NETWORKS OF PAST PROFESSIONAL COLLABORATIONS AND LOAN CONTRACT TERMS

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ABSTRACT

Francisco Dimas Pena Romera: Networks of past professional collaborations and loan contract terms.
(Under the direction of Wayne R. Landsman)

I use measures of structural centrality from network theory to examine whether the location of a lead arranger in its network of past syndicate collaborations affects loan characteristics and outcomes. I hypothesize that more central lead arrangers have access to better information channels that help mitigate adverse selection and moral hazard concerns, and lead to improved financing terms. I find that lead centrality is an important factor in explaining both price and non-price loan terms. Loans granted by more central lead arrangers charge lower spreads than otherwise comparable loans granted by more peripheral arrangers. In addition, more central arrangers grant loans that are typically larger, have longer maturities, and have a lower incidence of restrictive covenants and collateral requirements than loans granted by peripheral arrangers, which suggests that price concessions are not merely substituting for more restrictive clauses elsewhere in the contract. To mitigate the potential for alternative explanations for the effect of lead centrality on spread, I conduct several cross-sectional tests to determine whether the effect is stronger when the value of the information obtained through the network of past collaborations is higher. I hypothesize that information obtained through networks of past collaborations is higher when the borrower is less transparent and harder to screen, and when the lead arranger is ex-ante less informed about the borrower. I find evidence consistent with each of these predictions. Finally, I find that controlling for observable risk characteristics, ex-post loan

performance increases with the centrality of the lead, which is consistent with central leads having access to better information at origination.

To my mom and the rest of my crazy Canarian family, because they love me the same when I succeed and when I fail. To the handful of mentors that took a gamble on me and pushed me to places that would otherwise be unavailable to me. To the alligator, for helping me stay sane, and because without her all my graphs would look like Christmas trees.

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CHAPTER 1: INTRODUCTION

I use measures of structural centrality from network theory to examine whether the location of a lead arranger in its network of past loan syndicate collaborations affects loan characteristics and outcomes.

The syndicated loan market is an ideal setting in which to study information flows through networks of professional collaborations. In a syndicated loan, a bank, acting as a lead arranger, typically originates and sells off portions of the loan to other lending institutions. Teams in lending institutions engage in long term relationships with each other when they repeatedly collaborate in loan syndicates. Lending institutions that collaborate in syndicates must agree on the terms of the loan at origination, must coordinate monitoring efforts as the loan matures, and must vote on amendments and waiver requests when covenant violations occur. The structure of syndicate collaborations can be thought of as a network in which each lending institution is a node, and two nodes are connected if they have collaborated in a loan syndicate in the past. Characterizing syndicate collaborations as a network is useful because network theory has developed a variety of measures that capture the extent to which a node has a more influential position in the network, that is, measures of structural centrality (see Freeman (1978 and Jackson (2010)). Several studies in finance and accounting have began exploring the extent to which individuals or firms in more central positions in the network either have access to better resources and information channels (see, for example, Hochberg, Ljungqvist, & Lu (2007) and Larcker, So, & Wang (2013)), have greater ability to disseminate noisy information (Bajo, Chemmanur, Simonyan, & Tehranian (2016), or use their positions of influence for entrenchment purposes (El-Khatib et al., 2015).

In this study, I hypothesize that lead banks in more central positions in the network of past syndicate collaborations have access to better information channels that are valuable in pricing debt claims and structuring loan contracts. Specifically, If networks of past syndicate collaborations promote information sharing between teams in lending institutions, then a lead arranger in a more central position in the network of former syndicate collaborations could be in an advantageous position to extract information useful in the valuation of debt claims, relative to arrangers in more peripheral positions.

There are a number of ways in which valuable information could be moving through networks of past syndicate collaborations. For example, employees at connected institutions could directly share their knowledge about the quality of the borrower, about the prospects of the sector, or about the market appetite for specific loans. In addition, the networks could lower the cost of gathering information, for instance, it may take fewer calls, or prospective lenders may be more forthcoming with their knowledge and expertise when communicating with a former syndicate partner. Networks of past collaborations could make it easier for a lead arranger to obtain information about similar deals that have recently taken place and this could be helpful because comparable deals serve as a useful pricing benchmark. Moreover, the network can assist the arranger in obtaining information about the exposures of prospective banks to specific industries, geographies, borrowers, as well as changes in credit policies at such banks, all of which facilitate the arranging bank's ability to predict which set of banks are likely to participate in the loan and what price will clear the market.

Consistent with this argument, several practitioners have noted that the well-connectedness of a lead arranger with its peer lending institutions is key for loan pricing, and that information sharing is the main reason why. For example, when describing the pricing strategies of syndicating teams in lead arranger institutions, Campbell & Weaver (2013) pp 260 notes that: “Enquiries with other banks can thus be undertaken only on the basis of trust between the individuals concerned and it is this feature of the market which is perhaps the most important for a syndication unit, the establishment of a rapport with competitors which does not breach the competitive spirit of the market (any collusion as to pricing being, of course, unacceptable and contrary to competition law) and yet provides for a two-way flow of information”. 1

Motivated by the above assertions, I seek to explore the extent to which the well-connectedness of the lead arranger affects loan characteristics and outcomes, an issue that has received limited research effort. Some notable exceptions are worth mentioning. First, Engelberg, Gao, & Parsons (2012) explores how past social ties between the top management teams at banks and borrowing firms affect loan contract terms. Second, Godlewski, Sanditov, & Burger-Helmchen (2012) explores the role of bank lending networks as a measure of their experience and reputation in a sample of French syndicated deals. Third, a recent study by Houston et al., (2017) shows that banks whose directors have more shared social connections partner more frequently in the syndicated loan market, and that more central banks in the network of social connections take lead roles more frequently in syndicates.

I expand the above literature by computing measures of lead centrality in the global network of syndicate collaborations and exploring how lead centrality measures affect a broad set of loan contract terms in a comprehensive sample of 41,447 US loans from 1987 to 2016. I

[1] Additional examples of practitioners emphasizing the value of networks of past collaborations are available in Appendix B.

find that lead centrality is an important factor in explaining loan contract terms. Specifically, loans granted by more central lead arrangers in the network of global syndicate collaborations charge a lower loan spread than otherwise comparable loans granted by more peripheral arrangers in the network. A one standard deviation increase in the composite measure of lead centrality is associated with between an 11 bps and a 13 bps decrease in the loan spread charged. This finding is consistent with more central lead arrangers having access to better information channels that mitigate financing frictions, and at least part of the information benefits being passed on to borrowers in the form of lower loan spreads.

To reduce concerns that the result of lead centrality on spread is driven by omitted correlated variables, I conduct a battery of robustness tests. First, I control for a large set of firm-, loan- and bank- variables that prior literature has found to predict interest spreads. Second, I include several proxies for the reputation of the lead bank holding company based on prior literature (Bushman and Wittenberg-Moerman, 2012; Ross, 2010), and find that the effect of centrality on spread remains significantly negative. Third, I drop observations arranged by the largest lead bank holding companies, and observations in which there are more than one bank in a lead role in the syndicate. Fourth, I estimate a specification that inserts lead arranger fixed effects, to control for time invariant lead arranger level con-founders. Fifth, I create a dichotomous treatment variable (i.e., High Centrality) and use entropy matching to ensure that the covariates are balanced in the treatment and control sub-samples. Sixth, I keep only rated firms and estimate a specification with Industry×Rating×Year fixed effects. In all specifications, the effect of lead centrality on loan spread remains significantly negative.

In addition, I find that arrangers in a more central position in the network of past syndicate collaborations grant loans that are typically larger, have longer maturities, and have a lower incidence of restrictive covenants and collateral requirements than otherwise comparable loans granted by more peripheral arrangers. This is important because showing that non-price loan terms such as loan amounts, loan maturities, loan covenants and collateral requirements respond to centrality in the same way loan spread does, helps mitigate concerns that any price concessions warranted by more central leads are merely substituting for other, more restrictive non-price clauses elsewhere in the loan contract. If those trade-offs do occur, then the net effect of lead arranger centrality on loan terms becomes uncertain.

To further substantiate my inferences and mitigate the potential for alternative explanations for more central lead arrangers charging a lower loan spread than peripheral arrangers, I conduct several additional tests to determine whether the effect of lead centrality on spread is stronger when the value of the information obtained through the leads network is likely to be higher.

First, I predict that the information obtained from networks of past syndicate collaborations is likely higher when borrowers are relatively less transparent and harder to screen. I find evidence consistent with this prediction. Specifically, the effect of lead centrality on spread is higher for borrowing firms that are relatively less followed by analysts, for firms that do not have an S&P credit rating, for firms in high tech industries, for firms involved in R&D activities, and for firms whose financial statements are not audited by a Big5 audit firm.

Second, I predict that the information obtained from networks of past syndicate collaborations is likely higher when the lead lender is ex-ante relatively less informed about the borrowing firm. This can occur when the lead arranger is new to the industry of the borrower, new to the geography, when the lead arranger is not a local bank, or when the lead arranger is not a relationship bank. Consistent with lead arrangers extracting valuable information through their network of past syndicate collaborations, I find evidence supporting each of these predictions.

Third, I explore the possibility that the effect of lead centrality on spread is primarily driven by the ability of more central lead arrangers to use their well-connectedness to mitigate ‘within syndicate’ information asymmetries (i.e., information asymmetries between better informed lead arrangers and less informed syndicate participants). I re-run my main analysis, but I focus on a sub-sample of loans for which I expect within-syndicate information asymmetries to be either low or nonexistent. Specifically, I focus on loans granted to New Firms, that is, loans with an origination date that is earlier than three years after the borrowing firms’ IPO, as well as loans in which the lead arranger is the sole lender. The effect of lead centrality on loan spread remains significantly negative in both of these sub-samples. This mitigates the possibility that the effect of lead centrality on loan interest spread is solely driven by more central lead arrangers using their well-connectedness to reduce within syndicate information asymmetries, and suggests that at least part of the benefits of lead centrality stem from lead arrangers extracting (rather than only disseminating) information from their network of past collaborations.

Finally, I explore the relation between lead centrality and ex post loan performance, in an attempt to understand whether the price (and non-price) concessions granted by more central lead arrangers are a good decision ex-post. The findings reveal that, controlling for observable firm-, loan- and bank- level characteristics, lead arranger centrality is significantly negatively associated with the probability that the loan defaults during its life.

Taken together, this study’s findings contribute to the literature by exploring the extent to which loan contract terms are affected by networks of past professional relationships that emerge when teams in lending institutions collaborate in loan syndicates. While, as noted above, practitioners have emphasized the importance of information flows through networks of lending institutions for the success in the loan syndication business, there has been limited research effort directed to exploring whether there is broad sample evidence of such assertions.

CHAPTER 2: RELATED LITERATURE AND PREDICTIONS

Two streams of literature are the most relevant antecedents to this paper. The first is the stream of literature that explores the extent to which social ties between agents and firms have implications for capital markets. The second is the emerging literature that uses graph theory and measures of structural centrality to capture the extent to which certain individuals or firms have better access to resources and information.

2.1 Inter-personal linkages in finance and accounting

Numerous studies focus on the role of inter-personal connections and their effect on capital markets. For example, Cohen et al., (2008) studies portfolio allocation decisions of mutual fund managers that share past educational connections with corporate board members (such as when fund managers and corporate board members have a common alma-mater). Consistent with connected fund managers having access to better information channels through their network of past educational connections, the findings reveal that managers place more concentrated bets on connected stocks and that trades on connected positions outperform trades on unconnected positions. In a similar vein, Cohen and Malloy, (2010) shows that sell-side analysts use their network of past educational connections to gather information about the firms that they analyze. The study finds that sell side analyst with shared past educational ties issue more accurate recommendations. On the other hand, several studies uncover some of the negative consequences that arise from social connections. For example, Hwang and Kim, (2009) shows that when board members share social connections with the CEO, the monitoring effectiveness of the board is weaker. Similarly, Guan et al., (2016) shows that audit quality is compromised when auditors and clients share past educational connections.

More closely related to this study are studies that explore the role played by social connections in the syndicated loan market. For example, Engelberg et al., (2012) shows that when banks and borrowers share past educational connections, interest rates and other loan terms are considerably reduced. Houston et al., (2017) shows that bank with social connections partner together in the syndicated loan market more frequently and that banks in more central positions in the network of social connections contribute more to the systemic risk of the system.

Although the studies described here focus on the existence of an explicit social link between top individuals at firms (for example, in Engelberg et al., (2012) the top managers of a bank and a borrowing firm either share a past social connection or they do not), a growing stream of literature considers the network structure that emerges from the overall set of connections between firms or agents.

2.2 Networks in finance and accounting

Several studies use networks of connections to compute measures of structural centrality that capture the extent to which top individuals at firms are in more influential positions in the overall network, and purport that firms with individuals in more influential positions have access to better resources and information channels. [2] For example, Larcker et al., (2013) shows that firms with more central boards of directors in the network of shared directorates earn superior risk-adjusted returns than firms whose boards have more peripheral positions. On the other hand, El-Khatib et al., (2015) shows that more central CEOs in the network of social connections use

[2] See Freeman, (1978) for a discussion of the notion of structural centrality, and Jackson, (2010) for a comprehensive treatment of the literature in network theory.

their positions of influence to engage more frequently in empire building and value-decreasing M&A activities.

The literature outlined thus far focuses on the role of social connections between top individuals in firms (i.e, directors, CEOs, top executives etc.). However, many important decisions are not made at the highest levels of the chain of command, and relevant information sharing happens at lower levels in the hierarchy of organizations as well. More importantly, while the above literature emphasizes the importance of social connections, for example when the top management in two firms share an alma-mater, the literature largely neglects that much of the information sharing between organizations occurs from *professional* connections, rather than *social* connections, such as when the teams of two firms repeatedly collaborate in projects. If information sharing occurs between teams of mid-ranked individuals engaged in repeated collaborations, then it is possible that more central firms in the network of professional collaborations have access to better information channels than firms in more peripheral positions in the network. This perspective has received much less research effort. Some notable exceptions are Bajo et al., (2016); Chuluun, (2015); Godlewski et al., (2012); Hochberg et al., (2007). Hochberg et al., (2007) shows that venture capital firms in more central positions in the network of VC collaborations make investments that perform significantly better (higher likelihood of exit through IPO or sale to another company) than VC firms in more peripheral positions. Godlewski et al., (2012) explores the role of bank lending networks as a measure of their experience and reputation in a sample of French syndicated deals. Bajo et al., (2016) and Chuluun, (2015) study how the location of the IPO book-underwriter in the network of investment banks that collaborate in IPO syndicates affects IPO outcomes.

I expand the literature that explores the role of networks of professional collaborations by focusing on the syndicated loan market, a setting in which repeated collaborations between the teams of lending institutions is particularly prominent. Specifically, I study whether the location of the lead arranger in the global network of peer syndicate lenders has implications for loan characteristics and outcomes.

Before outlining my motivation and predictions it is useful to provide some institutional background on the functioning of the syndicated loan market.

2.3 Background on the syndicated loan market

Corporate loans remain the primary source of funds for corporations. Prior to the 1980's, the lending market was dominated by large commercial banks that granted loans and held them to maturity. Now, syndicated loans in which a bank, acting as a lead arranger, originates and sells off pieces of the loan to other lending institutions, are a sizable portion of the market.

Syndicated lending typically involves several important stages. [3] First, in a *pre-mandate stage*, a borrower expresses its need from the syndicated loan market and solicits bids from one or multiple banks that compete for the mandate. Banks competing for the mandate gather information about the purpose of the loan, the credit quality of the borrower, as well as current market conditions that may affect the banks ability to offload portions of the loan to other lending institutions either during the syndication phase or through the use of the secondary loan market after the syndication has been completed. Once all pertinent information has been gathered, competing banks submit a bid for the mandate. The bid typically involves both a pricing range as well as a syndication strategy. The syndication strategy includes a proposed list

[3] see Campbell and Weaver, (2013) for a more comprehensive discussion of the syndicated loan market, its evolution and documentation, as well as a detailed discussion of each of the stages involved in the syndication process.

of prospective lenders predicted to have an interest in joining the syndicate and acquiring a portion of the loan. Once the mandate has been awarded (i.e, when the borrower selects a winner among the competing bids), the mandated lead arranger prepares an '*information memorandum*' that contains all pertinent information about the borrower that will be relevant to prospective banks and lending institutions. [4] It has become increasingly prevalent that the borrower and the lead arranger organize a roadshow in which the borrower meets with prospective lenders and presents its forecast and financial performance followed by a Q&A session. After borrower and loan information has been disseminated to prospective lenders, a term sheet and formal invitation letters are sent out to prospective lenders that can choose to participate in the loan in various amounts. Upon the successful signing of the transaction, a member of the syndicate group is assigned the '*agent*' duty. The agent is in charge of coordinating the administration of the facility, gathering covenant compliance information and disseminating it to the lender group, collecting fees, arranging for covenant waivers and amendments in the event of technical default, etc. In addition, the secondary loan market has become increasingly important in the *post signing phase*. The secondary loan market allows lenders to offload portions of their loans to other bank and non bank institutional investors should the need to reduce exposure to a specific sector, borrower or geography arise (Parlour and Plantin, (2008)).

2.4 Motivation and predictions

The syndicated loan market is an ideal setting in which to study information flows through networks of professional collaborations. Teams in lending institutions engage in long

[4] The information memorandum frequently contains material, non-public information such as cash flow projections, interim performance measures, etc. This information memorandum is sent out to an agreed upon list of banks, who must sign confidentiality agreements. However, several research papers have raised concerns with information leaking to the market around loan originations and amendments, specially when non bank institutions are involved (see, for example, Bushman et al., (2010); Ivashina and Sun, (2011); Landsman et al., (2017) and Massoud et al., (2011).

term relationships when they jointly fund loans. The structure of syndicate collaborations can be thought of as a network in which a lending institution is a node, and two nodes are connected if they collaborate in a syndicate. To the extent that syndication networks facilitate information sharing, a more central lead arranger in the network of former syndicate collaborations could be in a better position to extract information useful in the valuation of debt claims. That is, information sharing in the network of former syndicate partners grants central lead arrangers access to better information about the credit risk of the borrower and/or market appetite for loans.

There are a number of ways in which valuable information could be moving through networks of past syndicate collaborations. For example, employees at connected institutions could directly share their knowledge about the quality of the borrower, about the prospects of the sector, or about the market appetite for specific loans. In addition, the networks could lower the cost of gathering information, for instance, it may take fewer calls, or prospective lenders may be more forthcoming with their knowledge and expertise when communicating with a former syndicate partner. Networks of past collaborations could make it easier for a lead arranger to obtain information about similar deals that have recently taken place and this could be helpful because comparable deals are typically a useful pricing benchmark. Moreover, the network can assist the arranger in obtaining information about the exposures of prospective banks to specific industries, geographies, borrowers, as well as changes in credit policies at such banks, all of which facilitate the arranging bank’s ability to predict which set of banks are likely to participate in the loan and what price will clear the market.

Several practitioners have noted that well-connectedness with peer lending institutions is key for loan pricing, and that information sharing is a critical reason why this is the case.

For example, consistent with syndicating units at lead arranger institutions gathering information through their network of peer institutions, Campbell and Weaver, (2013) pp 260 notes that: *"Enquiries with other banks can thus be undertaken only on the basis of trust between the individuals concerned and it is this feature of the market which is perhaps the most important for a syndication unit, the establishment of a rapport with competitors which does not breach the competitive spirit of the market (any collusion as to pricing being, of course, unacceptable and contrary to competition law) and yet provides for a two-way flow of information"*.

Appendix B contains additional examples of practitioners highlighting the importance of relationships with peer institutions for the success in the banking business. Several of the examples explicitly mention that nurturing a network of contacts and developing relationships of trust with peer institutions is fundamental in order to gain access to timely information.

Motivated by the above assertions, my study seeks to explore the extent to which the well connectedness of the lead arranger affects loan characteristics and outcomes.

A vast number of theoretical studies have explored market failures and financing frictions that arise from adverse selection concerns when there is information asymmetry between entrepreneurs and financiers (see the seminal work of Akerlof (1970) and Spence, (1973), as well as applications to the corporate finance setting such as, Beatty and Ritter (1986); Leland and Pyle (1977); Myers and Maljuf (1984); Rock (1986), among others). If more central lead arrangers in the network of syndicate collaborations have access to better information channels that are valuable in screening borrowers and pricing debt claims, for example, because better information is useful in mitigating the adverse selection concerns described in the literature above, then more central arrangers should be willing to accept lower interest terms (holding all else constant). [5] Moreover, if competition in the lending market leads to some of the information benefits being shared with borrowers, then I expect a negative relation between lead arranger centrality and interest spread. This leads to my first hypothesis (all hypotheses are stated in alternative form):

Hypothesis 1: Lead Arrangers with more central positions in the network of syndicate collaborations charge a lower loan spread.

Interest spread is only one of multiple loan terms that are bargained in lending agreements. For example, when asset substitution and risk shifting are a concern, lenders may seek protection with the use of net worth and financial covenants (Smith and Warner (1979)), or by lending in lower amounts, shorter maturities, and by requiring more collateral backing. If more central lead arrangers have access to better information channels that are helpful in mitigating risk shifting and asset substitution, then I expect that loans granted by more central lead arrangers are larger, have longer maturities and have a lower incidence of restrictive covenants and collateral requirements than otherwise comparable loans granted by arrangers in more peripheral positions in the network. Note that testing whether non-price loan terms respond to centrality in the same way loan spread does, helps mitigate concerns that any price concessions warranted by more central leads are merely substituting for other, more restrictive non-price clauses elsewhere in the loan contract. If those trade-offs do occur, then the net effect of lead arranger centrality on loan terms becomes uncertain. This leads to my second hypothesis:

[5] The logical framework here parallels that in Petersen and Rajan, (1994) where relationship lenders have access to better information, and in Engelberg et al., (2012) where social ties between borrowers and lenders stimulate information flows.

Hypothesis 2: Lead Arrangers in more central positions in the network of past syndicate collaborations lend in larger amounts, over longer maturities, with lower incidence of restrictive covenants and with less frequent collateral requirements.

To further substantiate my inferences and mitigate the potential for alternative explanations as to why more central lead arrangers charge a lower loan spread, I conduct several cross sectional tests to determine whether the effect of centrality on spread is stronger in instances in which the access to better information channels is likely to be more valuable for lead arrangers. First, I expect the information obtained through networks of prior syndicate collaborations to be particularly valuable when borrowers are less transparent and harder to screen. This leads to my third hypothesis:

Hypothesis 3: The effect of lead arranger centrality on loan spread is more pronounced for firms that are less transparent and harder to screen.

Second, if lead arrangers use their network of past syndicate collaborations to acquire information that is valuable in loan pricing, I expect the value of the syndicate network to be higher in cases in which the lead arranger is ex-ante less informed about the borrower. This can occur when the lead arranger is new to the industry of the borrower, the geography, the lead arranger is not a local bank, or when the lead arranger is not a relationship bank. This leads to my fourth hypothesis:

Hypothesis 4: The effect of lead arranger centrality on loan spread is more pronounced when the arranger is ex-ante relatively less informed.

CHAPTER 3: RESEARCH DESIGN

3.1 Measures of Lead Arranger Centrality

A key element in my research design requires the computation of lead arranger centrality. To do so, I largely follow Bajo et al., (2016) and Hochberg et al., (2007), and consider each lending institution as a node in a network, and two lending institutions are connected when they collaborate in at least one common loan syndicate in the 5 years prior to a loan initiation. [6]

Because structural centrality is a multi-dimensional construct (see Freeman, (1978) for a discussion), I follow El-Khatib et al., (2015); Houston et al., (2017) and Larcker et al., (2013) and use three common centrality measures widely used in network theory. The first, *Degree*, simply measures the number of institutions that the focal institution is connected to, the second, *Betweenness*, measures the frequency with which an institution is located in the shortest path between other institutions, and the third, *Eigenvector*, measures the extent to which an institution is connected to institutions that are themselves *central*.

I describe each in turn with the use of a simple network.

[6] Dealscan provides unique identifiers for each lending institution involved in a loan. In addition, Dealscan also provides information about each institution's ultimate parent 'UltimateParentID', frequently a bank holding company. Because I consider the lending teams in subsidiaries and affiliated lending institutions to be sufficiently separated from those of their parent bank holding institutions such that information channels between these teams are more accurately measured at the coarser level, throughout my analysis I use the subsidiary identifiers to measure centrality. Plots A, B and C in Figure 1 illustrate the network structures that emerge from collaborations in the syndicated loan market during quarters 1988-Q4, 2008-Q4 and 2016-Q4, respectively. Note that in Figures 1, 2 and 3, I describe the evolution of the syndicated network using quarterly slices of the data. Quarterly slices, by restricting the number of nodes, make the plotting of the networks feasible. However, the tests in the main analysis of the paper are based on measures of centrality that use larger networks that span 5 years starting in the year prior to each loan initiation date.

3.1.1 Degree Centrality

Degree is the simplest measure of node centrality. The degree of a node in a network is simply the count of the number of its adjacent nodes, i.e., the number of distinct relationships a lending institution has established with other institutions through its collaboration in prior loan syndicates. An institution with relatively more connections has more communication channels through its partner institutions, and this likely improves an institutions' ability to extract and/or disseminate information through the network. Degree centrality is computed as follows:

$$Degree_i = \frac{\sum_{j \neq i} x_{i,j}}{n}, \qquad (1)$$

where $x_{i,j}$ is 1 when institutions i and j collaborate in at least one syndicate, and n is the number of nodes in the network.

In the example provided in figure 1, the un-scaled degree centrality score of node C is 3 because node C is connected to three other nodes, that is, nodes {B,E,D}.

3.1.2 Betweenness Centrality

Betweenness centrality measures the frequency witch which a node is located on the shortest path between any other two nodes of the network. Lending institutions that score high on *Betweenness* act as gatekeepers of information because an institution located between two other institutions (or clusters of institutions) can either facilitate or impede the information flow between institutions.

Betweenness Centrality is computed as follows:

$$Betweennness_i = \frac{\sum_{j \neq i: i \notin k, j} G_i(k,j) / G(k,j)}{(n-1)(n-2)/2}, \qquad (2)$$

where G(k,j) are all the shortest paths existent between nodes k and j, and $G_i(k,j)$ are all the shortest paths between nodes k and j that go through node i.

In the example provided in figure 1, the un-scaled betweenness centrality score of node F is 0.5. Note that node F is only in the shortest paths that connect nodes H and G and we can therefore disregard the rest of the nodes. There are a total number of 2 shortest paths from node H to node G (i.e., H → A → G and H → F → G), and a total of two shortest paths from node G to node H (i.e., G → A → H and G → F → H). Two out of the four shortest paths go through node F, and therefore the unscaled betweenness score of node F is 0.5. In addition, it is worth noting that while node B scores lower in degree centrality than, for example, node E (node, E has 3 friends while node B has only 2), node B has a larger betweenness centrality score than node E. This is because node B is more frequently in the shortest path between all nodes (betweenness of B is 16, whereas betweenness of E is 7). This illustrates the multi-dimensional nature of centrality. While node E has more direct contacts and could conceivably extract information from a larger number of institutions, node B is a gatekeeper because it lays in between two clusters of institutions and it could use its position to facilitate or impede information flows between those clusters.

3.1.3 Eigenvector Centrality

Eigenvector centrality measures the extent to which a node is connected to many nodes that are themselves central. That is, *Eigenvector* centrality is a variation of *Degree* centrality that weighs each partner node by its importance. Nodes that are connected to many peripheral nodes receive a lower score than nodes that are connected to many nodes that are themselves central, (see Bonacich, (1972) for computational details). Lending institutions that score high in *Eigenvector* centrality have greater ability to extract and or disseminate information since they have a access to better information channels through their connections to lending institutions that are themselves central. *Eigenvector* Centrality is computed by solving the following:

$$Eigen_i = \lambda^{-1} \sum_{j=1} \Omega_{i,j} Eigen_j, \tag{3}$$

where $\Omega_{i,j}$ is 1 when institutions i and j collaborate in at least one syndicate and λ is the largest eigen-value of the *adjacency matrix* Ω. An adjacency matrix (or matrix of connections) is simply a convenient way of describing a network. A network composed by a set of nodes or banks, B = {1,2,··· ,n} and a set of links (or relationships between banks) ω. If a link exists between banks i and j, we indicate it as (i,j) $\in \omega$. The adjacency matrix is the n × n matrix $\Omega = [\Omega_{ij}]$ whose element Ω_{ij} 6= 0 whenever (i,j) $\in \omega$. The network is un-directed if links are such that $\Omega = \Omega^T$, meaning that if bank A is connected to bank B, then bank B is also connected to Bank

A. A network is un-weighted if $\Omega_{i,j} \in \{0,1\}$, meaning that connections are binary, banks are either connected or they are not, but there is no weight assigned to the strength of the relationship. In the example provided in figure 1, it is worth noting that while node F and node E both have a score of 3 in degree centrality, the eigenvector centrality of node F is higher than that of node E (eigen of node F = 0.87, eigen of node E = 0.24). This occurs because despite having the same number of friends, the friends of node F are themselves more *popular* than those of node E.

3.1.4 NScore

Because as shown above, each of the three centrality measures described reflects different dimensions of centrality, following El-Khatib et al., (2015) and Larcker et al., (2013), I also create a composite measure of centrality, *NScore*, which is the average of the scaled ranks of each of the three measures. I rank banks in every calendar year by each of the centrality scores and assign the bank a rank value (i.e., the least central bank is assigned a 1, the second least central bank is assigned a 2, and so forth). I then divide the centrality rank by the number of distinct banks in each year in my sample. The rank transformation preserves the rank order of centrality scores and simplifies the interpretation of coefficients. *NScore* will be the primary centrality measure that I used throughout my analysis and when discussing results. Results are generally the same when using the normalized raw scores of each of the centrality measures, but *NScore*, by averaging accross the various dimensions of centrality, likely reduces noise when measuring the construct of interest. I compute *NScore* as follows:

$$NScore_i = \frac{10(Year\_Rank(Degree_i) + Year\_Rank(Betweenness_i) + Year\_Rank(Eigen_i)),}{3 \times \#\_Banks\_in\_Year} \tag{4}$$

Using the example provided in figure 1 as the network for a given year in my sample, degrank, eigenrank and betwrank are the scaled ranked values of degree, betweenness and eigenvector centrality respectively. Taking the average and multiplying by 10, we get *NScores* with values ∈ (0,10].

3.2 Testing for the effect of lead arranger centrality on loan interest spread

I generally base my research design in that of Bajo et al., (2016) and Chuluun,(2015). I test for the effect of *Centrality* on *Spread* by estimating the following equation by OLS:

$$\begin{aligned} Spread_{i,t} = \beta_0 + \beta_1 Centrality_{i,t-1} + \beta_{2-j} Loan\_Controls + \beta_{j+1,k} Firm\_Controls + \\ \beta_{k+1,l} Bank\_Controls + \beta_{l+1,m} Fixed\_Effects + \epsilon \end{aligned} \tag{5}$$

Each observation in the analysis corresponds to one loan (facility). [7] The dependent variable, *Spread*, is the interest margin over the LIBOR (London Inter-bank Offered Rate) for each loan. *Centrality* is each of the measures of lead arranger centrality described in section 3.1. β_1 reflects the change in spread for a one unit increase in the measure of lead arranger centrality. Hypothesis 1 predicts β_1 is negative, which is consistent with more central lead arrangers with access to better information channels accepting lower loan spreads than arrangers in more peripheral positions in the network.

Equation 3.5 includes a set of control variables for a variety of firm- and loan-specific characteristics that prior research identifies as affecting loan spread. Firms whose loans are arranged by more central lead arrangers could possess observable (and unobservable) characteristics that, while unrelated to the hypothesized mechanism by which more central lead arrangers can access better information channels, make them more attractive to more central lead arrangers and simultaneously affect interest spread. For example, it is possible that loans arranged by more central lead arrangers are larger and riskier. Inclusion of observable firm- and loan-specific characteristics that are correlated with loan spread and plausibly correlated with *Centrality* helps mitigate the potential for coefficient bias for the explanatory variable of interest, *Centrality*.

The firm characteristics are the ratio of long-term debt plus debt in current liabilities divided by total assets, *Leverage*; firm size as measured by the natural logarithm of total assets, *AtLog*; the ratio of property plant and equipment plus inventory divided by total assets, *Tangibility*; return on assets, *Roa*; an indicator variable for firms with negative income before extraordinary items, *Dloss*; the ratio of capx to total assets, *Capx Intens*; the Altman Z-score,

[7] I repeat my analysis at the package/deal level and results remain generally the same.

AltmanZ [8]; an indicator variable for firms with an S&P long-term rating greater than or equal to BBB-, *InvG*. In addition to time varying firm characteristics, I estimate eq. 3.5 using either industry fixed effects or firm fixed effects. Including industry (firm) fixed effects, controls for unobservable industry (firm) characteristics that are constant over time, *Industry FE* (*Firm FE*). All firm-level variables are measured as of the most recent annual financial reporting date prior to the loan origination.

I include loan characteristics that prior research identifies as being related to loan spread (see, for example Amiram et al., (2017); Nandy and Shao, (2007) and Shan et al., (2016)).

The loan characteristics I include in equation 3.5 are the natural log of the loan dollar amount, *LoanAmtLog*; the natural log of the loan term in months, *MatLog*; an indicator variable that equals one if the loan has a performance pricing provision, *DPerfpricing*; the natural log of then number of distinct lenders, *Nlenders*; an indicator variable that equals one if a loan is secured, *DSecured*; an indicator variable that equals one if a loan has covenants, *DCovenants*; a set of 37 indicator variables for loan purpose, e.g., whether a loan is used to finance an acquisition or whether a loan is used to execute a leveraged buyout; an indicator variable for whether a loan is a Term Loan B loan and below, *DTermB* [9]; an indicator variable of whether the loan is a Revolver/Line of credit, *DRevolver*; an indicator variable that takes value one if the parent bank holding company that arranges the loan is classified by dealscan as either *"Bank of America Merrill Lynch"*, *"JP Morgan"* or *"City"* or any of its predecessors (based on Ross,

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[8] Following Altman, (1968) I calculate Altman Z-score using the following equation: $(1.2 * (act - lct)/at) + (1.4 * re/at) + (3.3 * (ni + xint + txt)/at) + (0.6 * csho * prcc/lt) + (0.999 * sale/at)$.

[9] Landsman et al., (2017); Lim et al., (2014); Nandy and Shao, (2007) show that loans involving non-bank institutions charge an incremental spread relative to loans involving bank only lenders. Because non-bank institutions typically participate in Term loans B and bellow, the inclusion of *DTermB* helps control for the effect of non-bank institutional participation on spreads.

(2010)), *BH Reputation* [10]; an indicator variable that takes a value of one if the lead arranger has arranged at least one other loan by the same borrower in the previous 5 years , *Relationship*.

Equation 3.5 also includes year fixed effects, *Year FE* to control for common macroeconomic factors that explain *Spread*; as well as an indicator variable for loans involving multiple lending institutions with a lead role in the syndicate, *Multi Lead*, to control for systematic differences in loans with multiple lead arrangers). [11] All indicator variables take on the value of zero otherwise. Appendix A provides definitions of all variables used in equation 3.5 and following equations and details on how the variables are constructed.

3.3 Sensitivity analysis of the effect of centrality on loan spread and omitted correlated variables

Although, as described in section 3.2, I attempt to reduce omitted variable bias by including several firm-, loan- and bank- level control variables, my design does not include an instrument capable of identifying a causal relation. I further address the potential for omitted variable bias in several ways. First, I estimate a modified version of equation 3.5 in which I include lead arranger fixed effects to create a within-lead arranger research design. Lead arranger fixed effects control for all lead arranger level time invariant observable and un-observable characteristics that explain *Spread* and are correlated with *centrality*.

Multivariate matching techniques are a second approach frequently used in finance and accounting research to address omitted variable bias (see Roberts and Whited, (2013) for a

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[10] I repeat my analysis using variations of the control for lead arranger reputation, measured both at the parent Bank Holding Level as well as at the coarser Lead Arranger level. In all variations, inferences remain unchanged. Specifically, I replace BH Reputation with the market share of the bank holding company (BH MktShare) and with an indicator variable that equals one if the Market Share of the Lead Arranger is greater than 2% in the year prior to the loan origination, based on Bushman and Wittenberg-Moerman, (2012) (LA Reputation). I report the results of these variations in table 5. In addition, in untabulated analysis, I use the linking table provided by Schwert, (2018) to link in financial information of the largest lead bank holding companies in DealScan, for a sub sample that spans until 2012. I use the log of total assets of the lead Bank Holding company as a control variable for reputation and again, inferences remain unchanged.

[11] Findings in which I drop loans with multiple arrangers yield similar inferences.

discussion). While propensity score matching is the main form of multivariate matching used in accounting research, several recent studies indicate that propensity score matching often exacerbates differences between the individual variables used in the first stage of the propensity score estimation (e.g., Imbens and Rubin, (2015); King and Nielsen, (2016)). On the other hand, entropy balancing uses continuous weights that exactly account for inequalities in the first, second, and possibly higher moments of the co-variate distributions (Hainmueller, (2012)). My use of entropy balancing is complicated by the fact that my treatment variables are not binary. Despite this limitation, I seek to provide additional evidence of the robustness of my inferences. Thus, I create an indicator variable, *Hi Centrality* that takes the value of one if *Centrality* is above the sample median in a given year. I then include all the independent variables from Equation 3.5, with the exception of *Centrality*, as variables in the first-stage that estimates continuous weights to achieve covariate balance.

In addition, to mitigate the possibility that the effect of *Centrality* on *Spread* is driven by a few number of extremely large bank holding companies, or by syndicates involving multiple lead arrangers, both of which could be systematically different to the rest of the sample, I re-estimate equation 3.5 for sub-samples that a) exclude loans issued by the top 3 bank holding companies (based on Ross, (2010)), and b) exclude loans with syndicates that involve multiple banks in lead roles.

3.4 The effect of centrality on other non-price loan terms

I test for the effect of *Centrality* on other non-price loan terms using modified versions of equation 3.5. Specifically, I estimate the following equation:

$$\begin{aligned} Loan\_Feature_{i,t} = \beta_0 + \beta_1 Centrality_{i,t-1} + \beta_{2-j} Loan\_Controls + \\ \beta_{j+1,k} Firm\_Controls + \beta_{k+1,l} Bank\_Controls + \\ \beta_{l+1,m} Fixed\_Effects + \epsilon \end{aligned} \tag{6}$$

Loan Feature is equal to either a) the natural logarithm of the loan amount in million USD, *LoanAmtLog*; b) the natural logarithm of the loan maturity in months, *Matlog*; c) an indicator variable that takes a value of one if the loan has a financial or a net-worth covenant, *DCovenants*; and d) an indicator variable that takes a value of one if the loan is secured by collateral, *DSecured*. All control variables remain the same as those described in the section 3.2 for spread specifications, with the exception that in each case the dependent variable is excluded from the controls (i.e, *LoanAmtLog* can not be a control when *LoanAmtLog* is the dependent variable).

Hypothesis 2 predicts β_1 is positive in specifications in which *LoanAmtLog* or *MatLog* is the dependent variable, and negative in specifications in which *DCovenants* or *DSecured* is the dependent variable. These predictions are consistent with more central lead arrangers having access to better information channels that are helpful in mitigating the risks associated with debt contracting, and at least some of these information benefits being shared with borrowers both in the forms of lower spread, as well as with better non-price loan terms. Moreover, showing that non-price loan terms such as *LoanAmtLog*, *MatLog*, *DCovenants* and *DSecured*, respond to centrality in the same way *Spread* does, helps mitigate concerns that any price concessions warranted by more central leads are merely substituting for other, more restrictive non-price clauses elsewhere in the loan contract (see Amiram et al., (2017)). If those trade-offs do occur, then the net effect of lead arranger centrality on loan terms becomes uncertain.

3.5 Cross sectional tests - is lead centrality more valuable when borrowers are less transparent and harder to screen?

To test the prediction that the information obtained through networks of former syndicate collaborations is particularly valuable when borrowers are harder to screen and lack alternative sources of readily available information, I re-estimate equation 3.5 for sub-samples based on borrower transparency. I consider multiple measures for borrower transparency. The first measure, *Low Numest*, is based on prior studies that find evidence that analyst produce useful information for debt capital providers (see, for example, (Güntay and Hackbarth, (2010) and Mansi et al., (2011). *Low Numest* is an indicator variable that equals one when the number of analyst that follow the borrower in the year prior to the loan origination is below the sample median. The second measure, *No Rated*, is an indicator variable that takes a value of one when the firm's debt does not have an S&P long term rating in the year prior to loan origination. The third, fourth, and fifth measures: *Has Rd*, *Hi Tech* and *Big5* are based on prior studies that purport that borrowers with high R&D or in high tech industries are harder to screen (see Chuluun, (2015) and Sufi, (2007)) as well as studies that show that audit quality and accounting quality are priced by lenders (see, for example, Bharath et al., (2008); Chen et al., (2016); Graham et al., (2008); Longstaff et al., (2005); Minnis, (2011), among others). *Has Rd* is an indicator variable that takes a value of one when the firm reports positive R&D expenses in the year prior to loan origination. *Hi Tech*, is an indicator variable that takes a value of one when the firm is in a high tech two digit SIC code (I use the classification of high tech industries in Chuluun, (2015)). I measure audit quality using, *Big5*, which is an indicator variable that takes a value of one when the borrowing firm is audited by a Big5 auditor in the year prior to the loan origination. In each case, with the exception of *Big5*, the indicator variables take a value of one when the borrower is considered as having relatively low transparency, and zero otherwise. I test for cross sample differences in the coefficient of interest, *Centrality*. Hypothesis 3 predicts that the coefficient β_1_low_transparency_sample > β_1_high_transparency_sample.

3.6 Cross sectional test: is lead centrality more valuable when the lead is ex-ante relatively less informed?

To test the prediction that the information obtained through networks of past syndicate collaborations is particularly valuable when the lead is ex-ante relatively less informed about the borrower, the industry, or the geography, I re-estimate equation 3.5 for sub-samples based on the lead arrangers prior experience. I consider multiple indicator variables of a leads relative inexperience. The first, *No Relationship*, is based on studies that purport that relationship banks have access to proprietary information about the borrowers (see (Petersen and Rajan, (1994) and Rajan, (1992)). I measure *No Relationship* as an indicator variable that equals one when the lead is not a relationship bank, i.e, the lead bank has not arranged a loan for the same borrower in the past 5 years. The second measure, *New Industry*, is based on studies that show that industry peer information is valuable for lenders (see, (Shroff et al., 2016)). I measure a leads access to peer information as *New Industry*, which is an indicator variable that equals one when the lead has not arranged a loan in the same two digit SIC code in the past 5 years. The third and fourth, *New Geography* and *Non Local*, are based on the literature that finds that physical distance between lenders and borrowers is an important factor in the lenders ability to acquire soft information (see, Petersen and Rajan, (1994) and Stein, (2002)). I measure *New Geography* as an indicator variable that equals one when the lead has not arranged a loan in the same state in the past 5 years. I measure *Non Local* as an indicator variable that equals one when the bank and the borrower are in different states. In each case, the indicator variable takes a value of one when the lead arranger is considered to be ex-ante relatively less informed, and zero otherwise. I test for cross sample differences in the coefficient of interest, Centrality. Hypothesis 4 predicts that the coefficient β_{1}_inexperience-sample > β_{1}_experience-sample.

CHAPTER 4: SAMPLE AND DESCRIPTIVE STATISTICS

4.1 Sample Selection

I begin by obtaining all available loan pricing and contract data from DealScan, as well as information on the composition of each loan syndicate (lender names, lender identifiers, lender roles, etc.). The starting sample consists of approximately 345 thousand loans (or facilities), 237 thousand deals, with approximately 20 thousand distinct lenders and 88 thousand distinct borrowers. I compute measures of lead arranger centrality using this initial sample, which involves approximately 1.9 million loan-lender combinations. See section 3.1 for details on the construction of lead centrality measures. There is no straightforward way of identifying the lead arranger in a loan in cases in which more than one institution has a lead role in the syndicate. I perform sequential filters to identify the lead arranger (largely based in Amiram et al., (2017); Sufi, (2007) and institutional details on the common terminology used to describe syndicate members from Campbell and Weaver, (2013)).[12] Borrower accounting information used as control variables and in cross sectional tests are obtained from Compustat North America. I

[12] To identify lead arrangers, I first require that loans in my sample have at least one lender in a lead role, that is, at least one lender in the facility must be flagged by Dealscan as with either "Lead Arranger Credit" marked as "Yes", or "Agent Credit" marked as "Yes", or acting as either: Bookrunner, Agent, Arranger, Coordinating arranger, Lead arranger, Lead bank, Lead manager, Mandated Lead Arranger, Mandated arranger, Admin agent. If there is only one institution acting as "Mandated Lead Arranger", "Mandated Arranger" or "Bookrunner" then I keep this and delete all others. If duplicates still remain then keep only institutions with "Lead Arranger Credit" marked as "Yes" and delete all others. If duplicates still remain then keep only institutions with "Agent Credit" equal to "Yes" and delete all others. If duplicates still remain and the "bankallocation" variable is not missing in Dealscan, then keep the institution in a lead role that kept the largest fraction of the loan. If duplicates still remain then keep the institution that had a lead role in the largest number of distinct facilities in the year prior to origination. If duplicates still remain then keep the institution with a bank holding company that is most active in the syndicated loan market in the overall sample. It is worth noting that throughout my analysis I include a control variable Multi Lead in all specifications. Multi Lead is an indicator variable that takes a value of one when the syndicate contains more than one lending institution with a lead role in the syndicate. This mitigates concerns that loans with multiple leads are systematically different to loans with only one lead. In addition, I repeat my analysis using loans with only one lead arranger and results remain largely the same. Moreover, miss-classification of lead arrangers likely introduces noise in my measure of lead centrality which should bias regression coefficients in favor of the null.

merge Compustat and DealScan using the updated linking table provided by Chava and Roberts through WRDS (Chava and Roberts, (2008)). To be included in the sample, each loan facility observation must have non-missing data from DealScan and Compustat used to construct the primary variables in my analysis for the period 1987 to 2016. Table 2 provides details on the filters applied resulting in the final sample of 41,477 loans (facilities), 28,700 deals (packages) granted to 8,726 distinct borrowers.

4.2 Description of the evolution of the global network of loan collaborations

Figure 2 provides a description of the evolution of the global network of syndicate collaborations from 1987 to 2016. Figure 2 plots the quarterly networks that emerge from collaborations in loan syndicates. Each node is a lending institution and two nodes are linked when they participate in the same syndicate in the quarter. The size of the nodes depicted is proportional to their degree centrality (the number of distinct nodes that connect to the focal node within the quarter). The color of the nodes are based on their modularity class, an estimate of the extent to which nodes in the network are highly connected within a cluster but are sparsely connected with other clusters. Focusing on the 2008Q4 depicted in panel B of Figure 2, it is evident that geographic clusters emerge. The green section on the top of the plot contains mainly North American lending institutions (where banks such as Bank of America and JP Morgan show up as some of the most central players in the cluster). The black section in the bottom of the plot is mostly comprised by South American institutions, with the two largest Spanish banks Banco Santander and BBVA acting as gatekeepers and linking the South American cluster (black) with the European cluster (pink).

Figure 3 shows the evolution of the number of distinct lending institutions that participate in the syndicated loan market. It is worth noting that throughout the entire sample, the number of isolated lenders, that is, lenders that are not part of the fully connected component of the network, is very small (dark blue portion). It appears that a structural shift occurred in the mid 1990's, with the number of distinct lending institutions growing considerably (below 500 prior to 1990 but averaging around 1500 since the mid 1990's). This can be explained by the fact that prior to the mid 1990's, loan syndicates were comprised mainly of bank-only lenders. In the mid-1990s, non-bank institutional lenders, such as hedge funds, mutual funds, and finance companies, increased their participation in loan syndicates, largely because the introduction of loan ratings by rating agencies facilitated the syndication process and allowed for portfolio strategies to be applied to the valuation of the loan asset class (Campbell and Weaver, (2013); Nandy and Shao, (2007)). Also worth noting is the sharp drop in lending institutions and subsequent recovery during the global financial crisis around 2008.

Figure 4 shows the evolution of quarterly network descriptives with time. Panel A shows the evolution of network density. Density captures the proportion of potential connections that actually exist. It appears that density has dropped considerably between 1987 and the mid 1990's. While in the early years of my sample more than 30% of possible connections actually existed, the number has dropped to around 2% in the most recent quarters. Panel B shows that the average shortest distance between any two lending institutions has increased from around 1.7 in 1987 to around 2.7 in latter years, suggesting that institutions are on average, more distant from each other than what they used to be in the late 1980's. Panel C) yields a similar conclusion, the diameter of the giant component of the network (defined as the maximum shortest path between two nodes in the largest fully connected component of the network, i.e., the maximum smallest distance between nodes), has increased considerably from around 3 in 1987 to around 9 in the late 2010's.

4.3 Descriptive Statistics: primary variables in my analysis

Table 3 presents summary statistics for the sample of 41,447 loans originated between 1987 and 2016 with non-missing information on the variables used for my primary analysis. Panel A presents summary statistics for loan-, firm- and bank- variables relating to all loans in my analysis. The average loan spread is 222.8 bps with a standard deviation of 148.4 bps. The average leverage ratio is 0.308, 43% of the observations have a credit rating, and 19.5% of the 25 observations have investment grade ratings (BBB- or above). 34% of the observations are arranged by relationship lead arrangers, and around 8% of the loans are Term B and bellow, while around 70% are Revolvers. The average lead arranger in my sample is connected to 19.2% of all the institutions in the trailing 5-year network, with a standard deviation of 13.1%.

CHAPTER 5: EMPIRICAL RESULTS

5.1 The effect of lead centrality on loan spread

Table (4) presents results of OLS regressions investigating the effect of lead centrality on loan spread, i.e., the estimation of equation 3.5. The dependent variable in columns (1) through (5) is *Spread*, the interest margin over the LIBOR (London Interbank Offered Rate) for each loan. The main explanatory variable of interest is *Centrality*. *Centrality* is measured by *Degree* in column (1), by *Eigenvector* in column (2), by *Betweenness* in column (3), and by the composite measure, *NScore*, in columns (4) and (5). All specifications include firm-, loan-, and bank- level control variables, as well as industry, loan purpose, year, and *Multi Lead* arranger fixed effects, with the exception of column

(5), in which industry fixed effects are replaced by firm fixed effects. [13] The key finding in the table (4) regarding hypothesis 1 is that the coefficient on *Centrality*, β_1, is significantly negative in all five estimations, with t-statistics ranging from -4.25 to -14.18. [14]. In terms of economic magnitude, a one standard deviation increase in *NScore* (2.44, see table 3) is associated with between an 11 bps (2.44 × 4.59) and a 13 bps (2.44 × 5.32) decrease in loan spread. This effect is roughly equivalent to that of including a loan covenant in my sample. This

[13] For the sake of parsimony I do not tabulate the constant and fixed effects coefficients. Also, while I tabulate the results for the raw centrality scores in columns (1), (2) and (3) of this table, in subsequent tables I will only discuss the results for the aggregate measure *NScore*.

[14] Throughout, I include *, **, *** next to regression coefficients to indicate significance at the 10%, 5% and 1% level corresponding to a two-sided alternative. However, when discussing regression findings relating to coefficients for which I have signed predictions, e.g., the coefficient on *Centrality*, I use a five percent significance level under a one-sided alternative.

finding is consistent with lead arrangers in more central positions in the network being able to offer lower loan spreads than lead arrangers with more peripheral positions in the network.

5.2 Robustness of the effect of lead centrality on loan spread

Table (5) presents regression summary statistics for a battery of plausible variations of equation 3.5. All specifications in both panel A and panel B include firm-, loan- and bank- level control variables as well as *Loan Purpose*, *Multi Lead*, *Year* and *Industry* fixed effects except when otherwise noted below. [15]

Panel A Columns (1) and (2) present findings corresponding to versions of equation (3.5) in which I use alternative measures of the reputation of the lead bank holding company. Specifically, in column (1), I replace *BH Reputation* which is an indicator variable that equals one if the lead bank holding company is either *Bank of America Merrill Lynch*, *JP Morgan* or *Citi*, or any of their predecessors, based on (Ross, 2010), and include instead the variable *BH MktShare*, which is the market share of the lead bank holding company computed in the year before the loan origination. The estimated coefficient β_1, on *Centrality*, remains negative and significant (coefficient = -5.42, t-statistic = -9.72). In column (2), I replace *BH Reputation* with an indicator variable *LA Reputation* which takes a value of one when the lead arranger has a market share greater than 2% in the year prior to the loan origination, based on Bushman and Wittenberg-Moerman, (2012)). The coefficient β_1, on *Centrality*, remains negative and significant (coefficient = -6.33, t-statistic = -9.36). In addition, in untabulated analysis, I use the linking table provided by Schwert (2018) to add financial information of the largest lead bank holding companies by participation in DealScan. The linking table contains information for a sub

[15] For the sake of parsimony, in this table as well as in subsequent ones, I do not tabulate coefficients on control variables, as well as constant and fixed effects.

sample that spans until 2012. I re estimate equation 3.5 but using the natural log of total assets of the lead Bank Holding company, as an alternative control variable for lead arranger reputation and again, the coefficient on *Centrality* remains significantly negative.

To mitigate the possibility that results are driven by loans with multiple banks in lead roles in the syndicate, Panel A, column (3) estimates equation (3.5) but dropping observations in which *Multi Lead* is equal to one. Consistent with measurement error being introduced in *Centrality* in syndicates with multiple institutions acting in lead roles (because of miss-classification of lead banks), the coefficient on *Centrality* increases in magnitude and significance for the sub-sample of loans with only one lead bank (coefficient = -7.05, t-statistic = -11.38)To mitigate the possibility that results are driven by a small number of very large bank holding companies, in column (5), I remove all loans arranged by the largest three bank holding companies (i.e, keep only observations where *BH Reputation* equals 0). The coefficient on *Centrality* remains negative and significant (coefficient = -5.88, t-statistic = -10.31). To help reduce concerns of omitted correlated variables at the lead arranger level biasing the explanatory variable of interest, Panel B, column (1) estimates a variation of equation 3.5 that includes lead arranger fixed effects, thus creating a within lead arranger design. The identifying assumption here is that any unobservable bank level confounders are constant over time. The coefficient on *Centrality* remains negative and significant (coefficient = -3.83, t-statistic = -4.92).

Despite the fact that my treatment variable of interest is not dichotomous, in column (2) of Panel

B, I report the results of a variation of equation 3.5 in which I replace *Centrality* with an indicator variable, *Hi Centrality*, that is equal to one when the lead arrangers' *Centrality* is greater than the sample median by year. In column (3), I report results for a weighted specification that uses Entropy weights (based on (Hainmueller, 2012)), to achieve co-variate balance between *High Centrality* observations and *Low Centrality* observations in all covariates in equation 3.5. The coefficients on *Hi Centrality* remain negative and significant (coefficient = -9.68, t-statistic = -4.88 in column (2) and coefficient = -8.31, t-statistic = -4.51 in column(3)).

Finally, column (4) in Panel B presents results from estimating a modified version of equation 3.5 only for the sub-sample of observations with a non-missing long term credit rating. In addition, the estimation in column (4) includes a more demanding fixed effects structure than previous specifications. Specifically, I include *Industry* × *Rating* × *Year* fixed effects, creating a within *Industry-Year-Rating* research design. The coefficient of interest, *Centrality*, is identified by variation in *Centrality* for borrowers in the same industry, the same year and the same credit rating. The coefficient on *Centrality*, albeit smaller, remains negative and significant (coefficient = -3.21, t-statistic=3.44).

Overall, the combined evidence in tables 4 and 5 suggests that lead arrangers in more central positions in the network of past syndicate collaborations are able to offer lower loan spreads than arrangers in more peripheral positions. This findings are consistent with the well-connectedness of the lead arranger being an important factor in the pricing of debt claims, and in support of hypothesis 1, as well as the emphasis placed by practitioners when describing relationships between banks as fundamental for the success in the syndication business.

5.3 The effect of lead centrality on other, non-price loan terms

Table (6) presents regression summary statistics for the estimation of equation 3.6, investigating the effect of lead centrality on non-price loan terms (Hypothesis 2). All specifications contain the same set of firm- loan- and bank- control variables as in previous specifications (i.e, the same controls as those in table 4), with the exception of the control variable that corresponds to the dependent variable used in each case.

Panel A columns (1) and (2) correspond to specifications that investigate the effect of lead centrality on loan size, *LoanAmtLog*. Column (1) includes industry fixed effects, whereas column (2) includes firm fixed effects. The key finding in columns (1) and (2) regarding hypothesis 2 is that the coefficient on *Centrality* is positive and significant in both specifications (coefficient = 0.033, t-statistic=10.61 in column (1), and coefficient = 0.027, t-statistic=8.07 in column (2)). This findings suggest that arrangers in a more central position in the network of past syndicate collaborations loan in larger amounts than arrangers in more peripheral positions. In terms of economic magnitude, a one unit increase in *NScore* is associated with between a 3.3% and a 2.7% increase in the loan size.

Panel A columns (3) and (4) correspond to specifications that investigate the effect of lead centrality on loan maturity, *MatLog*. Column (3) includes industry fixed effects, whereas column (4) includes firm fixed effects. The key finding in columns (3) and (4) regarding hypothesis 2 is that the coefficient on *Centrality* is positive and significant in both specifications (coefficient = 0.016, t-statistic=8.25 in column (3), and coefficient = 0.01 t-statistic = 4.46 in column (4)). This suggests that holding other covariates constant, more central leads are able to grant loans with larger maturities than peripheral leads. In terms of economic magnitude, a one unit increase in *Centrality* is associated with between a 1% and a 1.7% increase in the loan maturity.

Panel B columns (1) and (2) correspond to specifications that investigate the effect of lead centrality on the probability that the loan contains a financial or net worth covenant, *DCovenant*. Column (1) includes industry fixed effects, whereas column (2) includes firm fixed effects. The key finding in columns (1) and (2) regarding hypothesis 2 is that the coefficient on *Centrality* is negative and significant in both specifications (coefficient = -0.006, t-statistic=-4.53 in column (3), and coefficient = -0.006, t-statistic=-3.97 in column (4)). This findings suggest that arrangers in a more central position in the network of past syndicate collaborations loan with fewer covenants than arrangers in more peripheral positions. In terms of economic magnitude, a one unit increase in *NScore* is associated with a 0.6% decrease in the probability of the loan containing a Covenant. Untabulated findings show that using *HI CENT*, an indicator variable that takes a value of one when *NScore* is above the mean in every year, leads to a 3.1% reduction in the probability of the loan having a covenant (t-statistic = -5.28).

Panel B columns (3) and (4) correspond to specifications that investigate the effect of lead centrality on the probability that the loan is secured, *DSecured*. Column (3) includes industry fixed effects, whereas column (4) includes firm fixed effects. The key finding in columns (3) and (4) regarding hypothesis 2 is that the coefficient on *Centrality* is negative and significant in both specifications (coefficient = -0.011, t-statistic=-8.67 in column (3), and coefficient = -0.008, t-statistic=-5.07 in column (4)). This findings suggest that arrangers in a more central position in the network of past syndicate collaborations loan with fewer incidence of collateral requirements than arrangers in more peripheral positions. In terms of economic magnitude, a one unit increase in *NScore* is associated with between a 1.1% and a 0.8% decrease in the probability that the loan is secured.

Overall, the evidence in table 3.6 suggests that lead arrangers in more central positions in the network of past syndicate collaborations are able to offer better non-price terms than arrangers in more peripheral positions in the network. This findings are consistent with the wellconnectednesss of the lead arranger being an important factor, not only for the pricing of debt claims, and in support of hypothesis 1, but also for non-price loan terms.

5.4 The effect of lead centrality on spread - conditional on borrower transparency

In this subsection, I present results from cross-sectional tests to determine if the effect of lead centrality on spread varies when the borrower is relatively less transparent and is harder to screen. Hypothesis 3 predicts that the value of lead centrality increases when the borrower is opaque. I use five measures of borrower transparency and, in each case, table 7 reports summary statistics for the estimation of equation 3.5 for the sub-samples of transparent and opaque borrowers, respectively.

Panel A Columns (1) and (2) correspond to sub-sample estimations based on the variable *Lo Numest*. The key finding in columns (1) and (2) is that the coefficient on *Centrality* is significantly higher in the opaque sub-sample with a low number of analyst following (coefficient = -3.29 in the high analyst sub-sample versus coefficient=-6.02 for the low analyst sub-sample, with a $\tilde{\chi}^2$ statistic for a test of sub-sample difference in coefficients = 15.83, p-value = 0.000)

Panel A Columns (3) and (4) correspond to sub-sample estimations based on whether the borrowing firm has a long term rating in the year prior to the loan origination. Firms without a credit rating are considered opaque. The key finding in columns (3) and (4) is that the coefficient on *Centrality* is significantly higher in the opaque sub-sample without a credit rating (coefficient = -3.06 in the rated sub-sample versus coefficient=-6.14 in the non-rated , with a $\tilde{\chi}^2$ statistic for a test of sub-sample difference in coefficients = 15.24, p-value =0.000)

Panel B Columns (1) and (2) correspond to sub-sample estimations based on whether the borrowing firm is in a high tech industry. Firms in high-tech industries are considered harder to screen and with lower accounting quality. The key finding in columns (1) and (2) is that, despite the fact that only 5310 observations remain in the high tech sub-sample, the coefficient on *Centrality* is significantly more negative in the high-tech sub-sample (coefficient = -5 in the non high-tech sub-sample versus coefficient=-6.91 in the high-tech sub-sample , with a $\tilde{\chi}^2$ statistic for a test of sub-sample difference in coefficients = 3.5, p-value =0.061).

Panel B Columns (3) and (4) correspond to sub-sample estimations based on whether the borrowing firm is an R&D firm. Firms with zero or missing R&D expenses are consider transparent, whereas firms with positive R&D expenses are considered relatively more opaque. The key finding in columns (3) and (4) is that the coefficient on *Centrality* is significantly more negative in the R&D sub-sample (coefficient = -3.95 in the non R&D sub-sample versus coefficient=-7.47 in the R&D sub-sample , with a $\tilde{\chi}^2$ statistic for a test of sub-sample difference in coefficients = 21.382, p-value =0.000).

Panel C Columns (1) and (2) correspond to sub-sample estimations based on whether the borrowing firm is audited by a Big5 audit firm in the year prior to the loan origination. Firms with BIG5 auditors are considered more transparent and therefore require lower screening effort. The key finding in columns (1) and (2) is that, despite the fact that only 5694 observations are in the non-BIG5 sub-sample, the coefficient on *Centrality* is significantly more negative in the non-BIG5 sub-sample (coefficient = -4.87 versus coefficient=-6.9, with a $\tilde{\chi}^2$ statistic for a test of sub-sample difference in coefficients = 4.04, p-value =0.044).

Overall, the evidence in table 7 suggests that the value of lead centrality is particularly high for firms that are less transparent and harder to screen, in support of hypothesis H3.

5.5 The effect of lead centrality on spread - conditional on measures of lead arranger prior expertise

In this subsection, I present results from cross-sectional tests to determine if the effect of lead centrality on spread varies when the lead arranger lacks geographic, industry or borrower expertise. Hypothesis 4 predicts that the value of a lead arrangers network increases when the lead arranger lacks prior industry, geography or borrower specific expertise.

I use four measures of lead arranger expertise and, in each case, table 8 reports summary statistics for the estimation of equation 3.5 for the sub-samples of relatively high vs low lead arranger expertise.

Panel A Columns (1) and (2) correspond to sub-sample estimations based on whether the lead arranger is a relationship bank. The key finding in columns (1) and (2) is that the coefficient on *Centrality* is significantly more negative for the sub-sample of non-Relationship arrangers (coefficient = -3.07 in the Relationship sub-sample versus coefficient = -5.94 in the non-Relationship sub-sample , with a $\tilde{\chi}^2$ statistic for a test of sub-sample difference in coefficients = 11.49, p-value =0.001).

Panel A Columns (3) and (4) correspond to sub-sample estimations based on whether the lead arranger has arranged at least one other loan in the same two digit sic code in the 5 years prior to the loan origination. The value of the information channels provided by the network of former syndicate collaborations is expected to be higher if the lead arranger is new to the industry. The key finding in columns (3) and (4) is that the coefficient on *Centrality* is significantly higher for the sub sample of loans issued by lead arrangers that are new to the Industry (coefficient = -4.6 in the Not New to Industry sub-sample versus coefficient=-7.96 in the New to industry sub-sample, with a $\tilde{\chi}^2$ statistic for a test of sub-sample difference in coefficients = 15.69, p-value =0.000)

Panel B Columns (1) and (2) correspond to sub-sample estimations based on whether the lead arranger has arranged at least one other loan in the same state in the 5 years prior to the loan origination. The value of the information channels provided by the network of former syndicate collaborations is expected to be higher if the lead arranger is new to the geography of the borrower. The key finding in columns (3) and (4) is that the coefficient on *Centrality* is significantly higher for the sub sample of loans issued by lead arrangers that are new to the geography (coefficient = -4.00 in the Not New to geography sub-sample versus coefficient=-7.96 in the New to industry sub-sample, with a $\tilde{\chi}^2$ statistic for a test of sub-sample difference in coefficients = 20.80, p-value =0.000)

Panel B Columns (3) and (4) correspond to sub-sample estimations based on whether the borrower is located in the same state as the lead arranger. The value of the information channels provided by the network of former syndicate collaborations is expected to be higher if the lead arranger is located in a different state. The key finding in columns (3) and (4) is that the coefficient on *Centrality* is significantly more negative in the out of state sub-sample (coefficient = -3.87 in the same state sub-sample versus coefficient=-7.45 in the out of state sub-sample , with a $\tilde{\chi}^2$ statistic for a test of sub-sample difference in coefficients = 12.77, p-value =0.000).

Overall, the evidence in table 8 suggests that the value of lead centrality is particularly high when the lead arranger lacks geographic, sector or borrower specific expertise, in support of hypothesis H4.

CHAPTER 6: ADDITIONAL ANALYSIS

6.1 Within-syndicate information asymmetries and skin in the game

One possible explanation for the association between lead centrality and improved financing terms is that lead centrality is helpful in mitigating financing frictions that arise from within-syndicate information asymmetries (Amiram et al., (2017); Ivashina, (2009) and Sufi, (2007)). That is, if central lead arrangers with better information channels are more effective at *disseminating* noisy information about borrowers to participant lenders, this could reduce price protection by participant lenders and lead to improved financing terms. A well known solution to the within-syndicate information asymmetry problem is for the lead arranger to have more skin in the game by holding a larger fraction of the loan at origination. In table 9, I explore the relation between lead arranger *Centrality* and the fraction of the loan held by the lead arranger at origination. Specifically, table 9 Columns (1) and (2) presents results of estimating equation 6.1 for the sub-sample of loans with available information in DealScan on the fraction of the loan held by the lead arranger at origination, *%Lead*.

$$\%Lead_{i,t} = \beta_0 + \beta_1 Centrality_{i,t-1} + \beta_{2-j} Controls + + \beta_{j+1,m} Fixed\_Effects + \epsilon \qquad (7)$$

The findings reveal that, consistent with lead centrality mitigating financing frictions that arise from within-syndicate information asymmetries, *Centrality* is negatively associated with the fraction of the loan held by the lead arranger at origination. A one unit increase in *Centrality* decreases the percentage of the loan held by the lead arranger in between 0.63% and 0.79%. In addition, in Column (3) of table 9, I estimate an augmented version of equation 6.1. The modification interacts the key explanatory variable (*Centrality*) in equation 6.1 with a composite measure of the opaqueness of the borrower, (*Opaque Comp*). *Opaque Comp* is equal to the sum of the five indicator variables of borrower opaqueness used in the cross-sectional tests outlined in hypothesis H3 (i.e., *Lo Numest, Has RD, Hi Tech, No _Rated, No Big5*). The key coefficient of interest in column (3) of table 9 is that on *Centrality* × *Opaque _Comp*. The findings reveal that the effect of *Centrality* on the fraction of the loan held by the lead increases with the opaqueness of the borrower, which is expected since 'within-syndicate' information asymmetries are greater for borrowers that are harder to screen.

While the evidence in table 9 is consistent with an *information dissemination* story in which more central lead arrangers use their positions of influence to mitigate within syndicate information asymmetries, this explanation need not be mutually exclusive from an *information extraction* story in which central lead arrangers gather valuable information through their network of past syndicate collaborations. I next examine a setting in which I expect *within-syndicate* information symmetries to be either low or nonexistent. Specifically, in Columns (1) and (2) of table 10 I re-estimate equation 3.5 in a sample of loans issued to New firms, i.e., loans whose origination date is smaller than three years after the firms' IPO date. In Columns (3) and (4) of table 10 I keep only loans in which the lead arranger is the sole lender. The key finding in columns (1) through (4) is that the coefficient on *Centrality* remains significantly negative in all specifications, which is consistent with at least part of the benefits of lead centrality stemming from *information extraction* rather than *information dissemination*, since within-syndicate information asymmetries are likely low in the new firms sub-sample, and non existent in the sole lender sub-sample.

6.2 Ex-Post Loan Performance

The finding that lead centrality is associated with better financing terms raises the question of whether such price and non-price concessions are warranted, that is, whether loans granted by more central lead arrangers perform better ex-post. Testing for ex-post loan performance is complicated by the fact that DealScan does not provide loan-level performance data. Despite this limitation, I follow Gao and Jang, (2018), and measure loan performance based on estimated defaults. I consider that a loan defaults when the borrowing firms' long term S&P credit rating drops to *Default* rate during the life of the loan. This limits my sample to the 22,141 loans with some credit rating information available during their life. Only 5.8% of the loans in my sample default. Table 11 reports summary statistics for the estimation of a linear probability model in which the dependent variable is an indicator variable *Default*, that is equal to one if the loan defaults during its life, and zero otherwise. The key finding in 11 is that the coefficient on *Centrality* is significantly negative, which I interpret as evidence consistent with more central lead arrangers having better information at origination.

CHAPTER 7: SUMMARY AND CONCLUDING REMARKS

This study addresses whether lead banks in a more central position in the global network of past syndicate collaborations offer more favorable financing terms than arrangers in more peripheral positions in the network. If networks of past syndicate collaborations stimulate information flows that mitigate financing frictions such as adverse selection and moral hazard concerns, then lead arrangers in a more central position in the network may be able to offer better financing terms than peripheral arrangers. I compute common measures of structural centrality from network theory using the global network of syndicate collaborations and test this prediction in a comprehensive sample of 41,447 US loans from 1987 to 2016.

I find that lead centrality is an important factor in explaining both price and non-price loan terms. Controlling for a battery of loan-, firm- and bank- level variables that prior literature has found to predict loan terms, I find that loans granted by more central lead arrangers charge a lower loan spread than otherwise comparable loans granted by more peripheral arrangers. I find that the result of lead centrality on loan spread is robust to an array of plausible variations in the estimation procedure aimed at mitigating the possibility that the result is driven by omitted correlated variable bias.

In addition, I find that arrangers in a more central position in the network of past syndicate collaborations grant loans that are typically larger, have longer maturities, and have a lower incidence of restrictive covenants than otherwise comparable loans granted by more peripheral arrangers. This is important because showing that non-price loan terms such as loan amounts, loan maturities and loan covenants respond to centrality in the same way loan spread does, helps mitigate concerns that any price concessions warranted by more central leads are merely substituting for other, more restrictive non-price clauses elsewhere in the loan contract. If those trade-offs do occur, then the net effect of lead arranger centrality on loan terms becomes uncertain.

To further substantiate my inferences and mitigate the potential for alternative explanations for more central lead arrangers charging a lower loan spread than peripheral arrangers, I conduct several additional tests to determine whether the effect of lead centrality on spread is stronger when the value of the information obtained through the leads network is likely to be higher.

First, I predict that the information obtained from networks of past syndicate collaborations is likely higher when borrowers are relatively less transparent and harder to screen. I find evidence consistent with this prediction. Specifically, the effect of lead centrality on spread is higher for borrowing firms that are relatively less followed by analysts, for firms that do not have an S&P credit rating, for firms in high tech industries, for firms involved in R&D activities, and for firms whose financial statements are not audited by a Big5 audit firm.

Second, I predict that the information obtained from networks of past syndicate collaborations is likely higher when the lender is ex-ante relatively less informed about the borrowing firm. This can occur when the lead arranger is new to the industry of the borrower, new to the geography, when the lead arranger is not a local bank, or when the lead arranger is not a relationship bank. Consistent with lead arrangers *extracting* valuable information through their network of past syndicate collaborations, I find evidence consistent with each of these predictions.

In addition, I find that the effect of lead centrality on spread remains significant in sub-samples with low or nonexistent *within-syndicate* information asymmetries, which suggests that at least part of the benefits of lead centrality stem from lead arrangers *extracting*, rather than *disseminating* valuable information through their network.

Finally, I find that holding observable covariates constant, ex-post loan performance increases with the centrality of the lead, which I interpret as evidence consistent with central leads having access to better information at origination.

Taken together, this study's findings contribute to the literature by exploring the extent to which loan contract terms are affected by networks of past professional relationships that emerge when teams in lending institutions collaborate in loan syndicates. While practitioners have emphasized the importance of information flows through networks of lending institutions for the success in the loan syndication business (see Campbell and Weaver, (2013) and Esty, (2001)) and the detailed discussion in section 2.4), there has been limited research effort directed to exploring whether there is broad sample evidence of such assertions.

APPENDIX A - VARIABLES

Table 1: Variable Construction

Variable name	Construction of Variable	Source
Network Vars		
Degree	The degree of a node in a network is simply the count of the number of its adjacent nodes, i.e, the number of distinct relationships a lending institution has established with other institutions through its collaboration in prior loan syndicates. I compute degree centrality using the R package Igraph as: $$Degree_i = \frac{\sum_{j \neq i} x_{i,j}}{n},$$ where $x_{i,j}$ is 1 when institutions i and j collaborate in at least one syndicate, and n is the number of nodes in the network. .	**Dealscan**
Betweenness	The betweenness of a node measures the frequency witch which a node is located on the shortest path between any other two nodes of the network. I compute betweenness centrality using the R package Igraph as: $$Betweennness_i = \frac{\sum_{j \neq i: i \notin k,j} G_i(k,j)/G(k,j),}{(n-1)(n-2)/2}$$, where $G(k,j)$ are all the shortest paths existent between nodes k and j, and $Gi(k,j)$ are all the shortest paths between nodes k and j that go through node i.	**Dealscan**
Eigenvector	*Eigenvector* centrality measures the extent to which a node is connected to many nodes that are themselves central. That is, Eigenvector centrality is a variation of Degree centrality that weighs each partner node by its importance (i.e, nodes that are connected to many peripheral nodes receive a lower score than nodes that are connected to many nodes that are themselves central). I compute Eigen centrality using the R package Igraph, measured as the solution to the following: $$Eigen_i = \lambda^{-1} \sum_{j=1} \Omega_{i,j} Eigen_j,$$ where $\Omega_{i,j}$ is 1 when institutions i and j collaborate in at least one syndicate and λ is the largest eigen-value of the *adjacency matrix* Ω. An adjacency matrix (or matrix of connections) is simply a convenient way of describing a network. A network composed by a set of nodes or banks, $B = \{1, 2, \cdots, n\}$ and a set of links (or relationships between banks) ω. If a link exists between banks i and j, we indicate it as $(i,j) \in \omega$. The adjacency matrix is the $n \times n$ matrix $\Omega = [\Omega_{ij}]$ whose element $\Omega_{ij} \neq 0$ whenever $(i,j) \in \omega$. The network is un-directed if links are such that $\Omega = \Omega^T$, meaning that if bank A is connected to bank B, then bank B is also connected to Bank A. A network is un-weighted if $\Omega_{i,j} \in \{0,1\}$, meaning that connections are binary, banks are either connected or they are not, but there is no weight assigned to the strength of the relationship.	**Dealscan**
Nscore	*Nscore* is the average of the ranks of the three centrality measures: $NScore_i =$ $$\frac{10(Year\_Rank(Degree_i) + Year\_Rank(Betweenness_i) + Year\_Rank(Eigen_i))}{3 \times \#\_Banks\_in\_Year}$$	**Dealscan**
Firm Vars		
Leverage	Leverage measured as long term debt plus debt in current liabilities over total assets. Computed as $(dltt + dct)/at$. Estimated the nearest year prior to the loan activation date.	**Compustat**
AtLog	The natural log of total assets. Computed as $\log(1 + at)$. Estimated the year prior to the loan activation date.	**Compustat**

Tangibility	Measured as the ratio of property plant and equipment plus inventory over total assets. Computed as $(\mathtt{ppent} + \mathtt{invt})/\mathtt{at}$. Estimated the year prior to the loan activation date.	**Compustat**
Roa	Return on Assets. Computed as $\mathtt{ib}/\mathtt{at}$. Estimated the year prior to the loan becoming active.	**Compustat**
DLoss	Indicator variable that takes a value of one for firms with negative income before extraordinary operations. Estimated the year prior to the loan activation date.	**Compustat**
Capx_Intens	The ratio of capx to total assets. Computed as $\mathtt{capx}/\mathtt{at}$. Missing capx values are set to zero. Estimated the year prior to the loan becoming active.	**Compustat**
AltmanZ	Altman's Z Score. Computed as $(1.2*(\mathtt{act}-\mathtt{lct})/\mathtt{at})+(1.4*\mathtt{re}/\mathtt{at})+(3.3*(\mathtt{ni}+\mathtt{xint}+\mathtt{txt})/\mathtt{at})+(0.6*\mathtt{csho}*\mathtt{prcc}/\mathtt{lt})+(0.999*\mathtt{sale}/\mathtt{at})$. Estimated in the year prior to the loan activation date.	**Compustat**
DInvG	Indicator variable that takes a value of one for firms with an S&P long term rating greater than or equal to BBB-. Estimated in the year prior to the loan activation date.	**Compustat**
Lo_Numest	Indicator variable that takes a value of one when the number of analyst following the firm prior to the loan activation date is bellow the median.	**Ibes**
No_Rated	Indicator variable that takes a value of one when the firm does not have an S&P long term rating. Estimated in the year prior to the loan activation date.	**Compustat**
Has_Rd	Indicator variable that takes a value of one when the firm reports positive R&D expenses. Estimated in the year prior to the loan activation date.	**Compustat**
Hi_Tech	Indicator variable that takes a value of one when the firm is in a high tech companies. Based on Chuluun (2015), SIC codes of 3571, 3572, 3575, 3577, 3578 (computer hardware), 3661, 3663, 3669 (communications equipment), 3671, 3672, 3674, 3675, 3677, 3678, 3679 (electronics), 3812 (navigation equipment), 3823, 3825, 3826, 3827, 3829 (measuring and controlling devices), 3841, 3845 (medical instruments), 4812, 4813 (telephone equipment), 4899 (communications services) and 7370, 7371, 7372, 7373, 7374, 7375, 7378 and 7379 (software) are considered High Tech.	**Compustat**
No_Rated	Indicator variable that takes a value of one when the firm does not have an S&P long term rating. Estimated in the year prior to the loan activation date.	**Compustat**
NBig5	Indicator variable that takes a value of one when the firm is not audited by a Big 5 Audit Firm. Estimated in the year prior to the loan activation date.	**Compustat**
Opaque_Comp	Composite measure of opaqueness equal to the sum of the five indicators *NBig5* + *No_Rated* + *Hi_Tech* + *Has_Rd* + *Lo_Numest*	**Compustat-Ibes**
New_Firm	Indicator variable that takes a value of one for loans granted to firms in a date earlier than IPO date plus 3 years. IPO date is equal to ipodate from Compustat when available, or equal to the first fiscal year end with a valid stock price variable (prcc_f).	**Compustat**
Default	Indicator variable that takes a value of one for loans whose firms' long term Rating drops to default category ("SD" or "D") during the life of the loan. Based on Gao and Jang (2018)	**Compustat**
Loan Vars		
Spread	Allindrawn spread above LIBOR of each loan (facility). All in drawn spread is the sum of the spread over LIBOR plus any annual fees paid to the lender group. Negative or zero values are set to missing	**Dealscan**

LoanAmtLog	Natural logarithm of the loan amount in million USD. Computed as $log(1 + facilityamt/1000000)$.	**DealScan**
MatLog	Natural logarithm of the loan maturity in months. Computed as $log(1 + maturity)$.	**DealScan**
DPerfricing	Indicator variable that takes value 1 if the loan has a performance pricing pricing provision.	**DealScan**
Nlenders	Number of lenders that participate in the loan (facility). Computed as $log(1 + Numberofdistinctlendersinfacility)$	**Dealscan**
Sole_Lender	Indicator variable that takes a value of one when the loan is a sole lender loan. I.e., when the bankallocation variable is equal to 100% or when the distribution method variable is equal to "Sole Lender".	**DealScan**
DCovenants	Indicator variable that takes a value of one when the loan has a financial or net worth covenant.	**DealScan**
DSecured	Idicator variable that takes value one if the loan is secured.	**DealScan**
Bank Vars		
BH_Reputation	Indicator variable that takes value one if the parent bank holding company that arranges the loan is either "Bank of America Merrill Lynch", "JP Morgan" or "City" or any of its predecessors. Based on Ross (2010)	**DealScan**
BH_MktShare	Market share of the parent institution that arranges the loan. Computed the calendar year prior to the loan activation date.	**DealScan**
LA_Reputation	Indicator variable that equals one if the Market Share of the lead arranger is greater than 2% in the year prior to the loan origination. Based on Bushman and Wittenberg-Moerman (2012)	**DealScan**
Relationship	Indicator variable that takes a value of one if the lead arranger has arranged at least one other loan by the same borrower in the previous 5 years.	**DealScan**
First_Indus	Indicator variable that takes a value of one if lead arranger has not arranged one or more facilities in the same industry in previous 5 years.	**DealScan**
First_Geo	Indicator variable that takes a value of one if the lead arranger has not arranged one or more facilities in the same city in the previous 5 years	**DealScan**
Fixed Effects		
Loan Purpose	Indicator variable that takes a value of one for each of loan purposes in my sample (i.e, whether a loan is used to finance an acquisition or whether a loan is used to execute a leveraged buyout, etc)	**DealScan**
Multi_Lead	Indicator variable that takes a value of one when there are multiple institutions with a Lead Role in the loan.	**DealScan**

APPENDIX B - EXAMPLES OF PRACTITIONERS DESCRIBING INFORMATION FLOWS IN NETWORKS OF LENDING INSTITUTIONS.

[1]. When describing the pricing strategies of syndicating teams in lead arranger institutions:

"*Enquiries with other banks can thus be undertaken only on the basis of trust between the individuals concerned and it is this feature of the market which is perhaps the most important for a syndication unit, the establishment of a rapport with competitors which does not breach the competitive spirit of the market (any collusion as to pricing being, of course, unacceptable and contrary to competition law) and yet provides for a two-way flow of information.*" Campbell and Weaver (2013) pp 260.

[2]. When describing the role personal relationships between individuals in lending teams of arranging institutions:

"*Unlike the worlds of bonds and equities, with their relatively straightforward products and large numbers of investors,* ***syndicated loans depend on fewer participants, and on the strength of relationships****.* ***It is a personal market, in which individuals still know each other and deals are distributed in telephone conversations or in e-mails,*** *rather than with a couple of mouse-clicks. While a bond syndication may last just a matter of hours, loans are usually less hurried and syndications still last days or weeks. The impact of technology on syndicated lending has therefore been different from that on other asset classes, and the* ***focus is still on the technology aiding communication between people, rather than communication between machines.***" Campbell and Weaver (2013) pp 66.

[3]. When Describing the importance of lending institutions nurturing a network of contacts to gather information about credit policies and market sentiment:

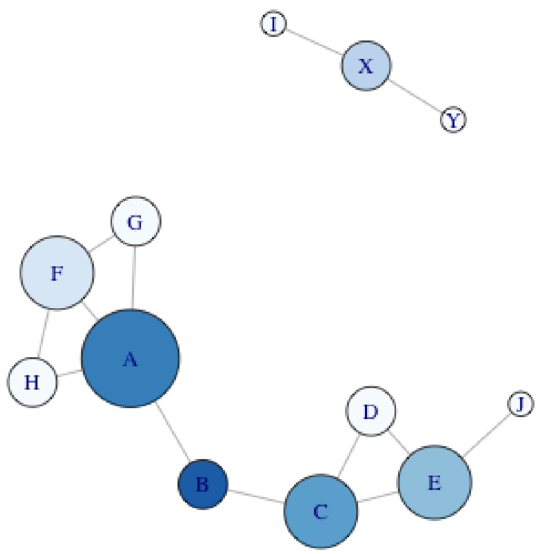
"*Detecting changes in lender behavior is a vital part of a syndicator's job, and to be successful,* ***a practitioner must create and maintain his or her own network of contacts in order to keep abreast of changes in market sentiment***". Campbell and Weaver (2013) pp 23.

[4]. Emphasizing the importance of close connections with other banks when syndicating large global project loans

The key to success in this business is being close to the market. ***This means being in touch with banks on a weekly, if not daily, basis****. We started with a universe of approximately 90 banks and* ***created a target lender list that might be interested in this deal.*** *We then partitioned the target list into commitment size categories and assigned participation probabilities for each category. This process gives us a sense of liquidity and an indication of whether the deal will clear the market. Based on our analysis for the Disney deal, we expected it would be oversubscribed by 57%. This kind of analysis* ***illustrates our closeness to the market*** *and our confidence in the deal."* Quote from Vivek Chandiramani, a member of the Chase Hong Kong team that arranged the $3.3 billion Hong Kong Disneyland project loan in the year 2000 Esty (2001) pp 88.

APPENDIX C- EXAMPLE OF A SIMPLE NETWORK

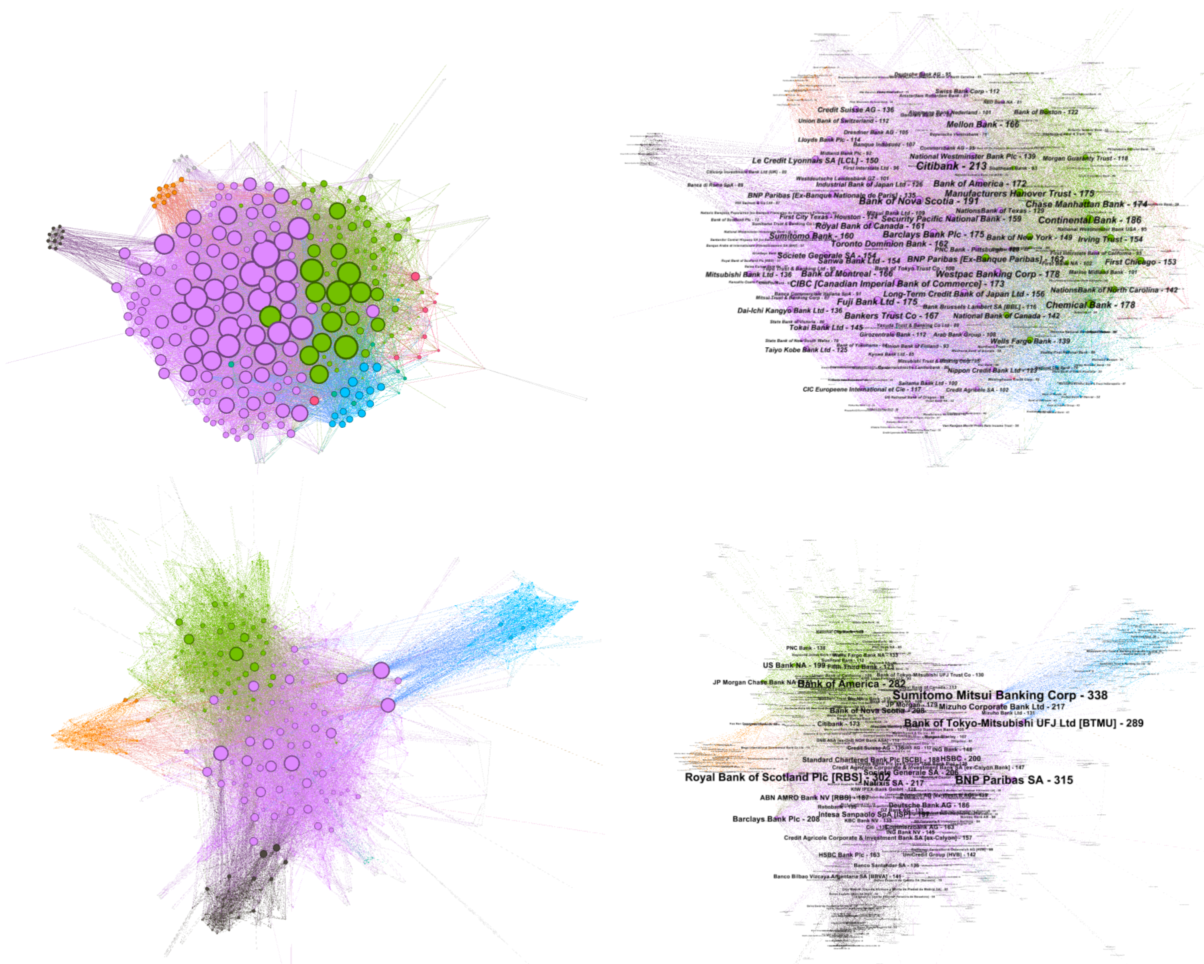
Figure 1: Measures of structural centrality



	Name	deg	betw	eigen	degrank100	eigenrank100	betwrank100	NScore	N	NC1
1	A	4	15.500	1	1	1	0.917	9.722	12	9
2	B	2	16	0.493	0.500	0.667	1	7.222	12	9
3	C	3	15	0.345	0.833	0.583	0.833	7.500	12	9
4	D	2	0	0.213	0.500	0.417	0.292	4.028	12	9
5	E	3	7	0.236	0.833	0.500	0.750	6.944	12	9
6	F	3	0.500	0.868	0.833	0.917	0.583	7.778	12	9
7	G	2	0	0.684	0.500	0.833	0.292	5.417	12	9
8	H	2	0	0.684	0.500	0.750	0.292	5.139	12	9
9	J	1	0	0.087	0.167	0.333	0.292	2.639	12	9
10	X	2	1	0	0.500	0.083	0.667	4.167	12	9
11	Y	1	0	0	0.167	0.250	0.292	2.361	12	9
12	I	1	0	0	0.167	0.167	0.292	2.083	12	9

APPENDIX D - MAIN TABLES AND FIGURES

Figure 2: Network of loan syndicate participants. Each node is a participant in the syndicated Loan market involved in at least one loan in a given quarter. Two nodes are connected when they are partners in at least one loan in the quarter. The size of the node (syndicate lender) is proportional to its degree centrality. The color of the nodes are based on their modularity class, an estimate of the extent to which nodes in the network are highly connected within a cluster but are sparsely connected with other clusters. Panel A) Corresponds to 1988 Quarter 4. Panel B corresponds to a quarter during the financial crisis 2008 Quarter 4 and panel C corresponds to 2016 Quarter 4.



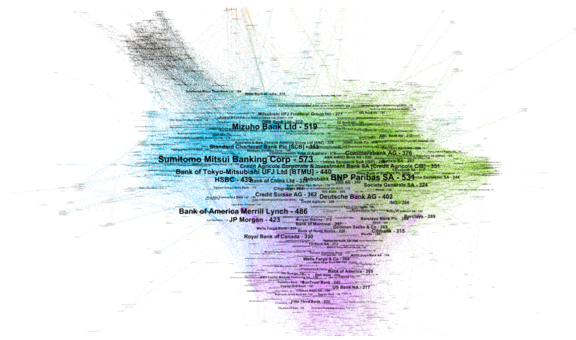


Figure 3: This figure presents the total number of institutions that collaborate in at least one loan with some other institution (in dark blue). In light blue I show how many of those institutions are connected to the largest connected component of the Network.

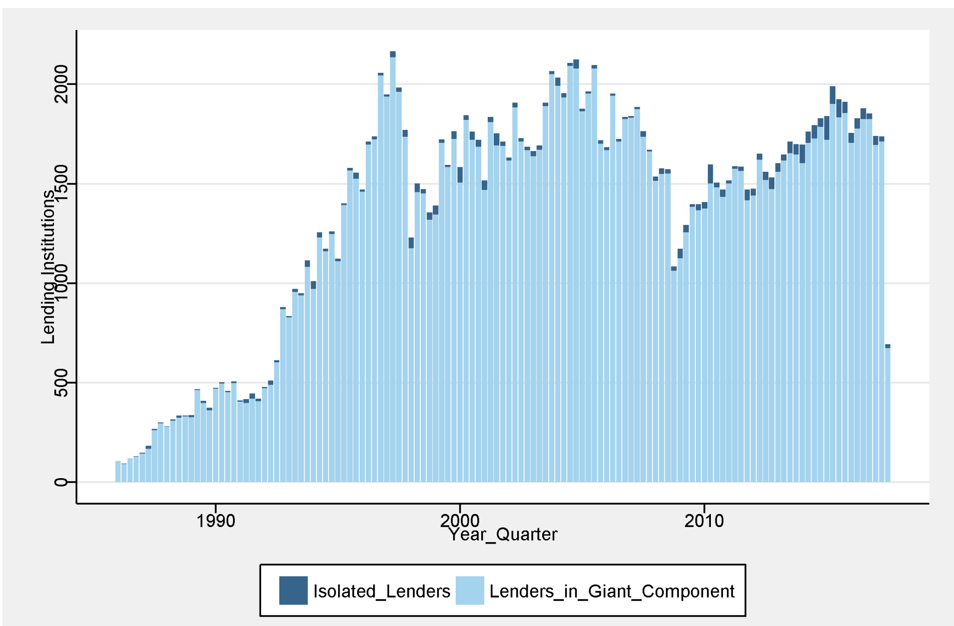


Figure 4: The figures below show the evolution of the network of syndicate Lenders with time. Fig A) shows the evolution of the network density. Density captures the proportion of the total number of edges that are realized (i.e, a bank was connected to around 30% of all other banks in the late 1990s, but this has decreased to around 2% in recent years. Fig B) sows the evolution of the Average Shortest Path of the Network. Fig C) shows the evolution of Network Diameter. Diameter is the maximum shortest path between two banks in the Network. Fig D) shows the evolution of Transitivity. Transitivity captures the average probability that if bank A is connected to bank B and bank B is connected with bank C, then what is the average probability that bank A is also connected with bank C.

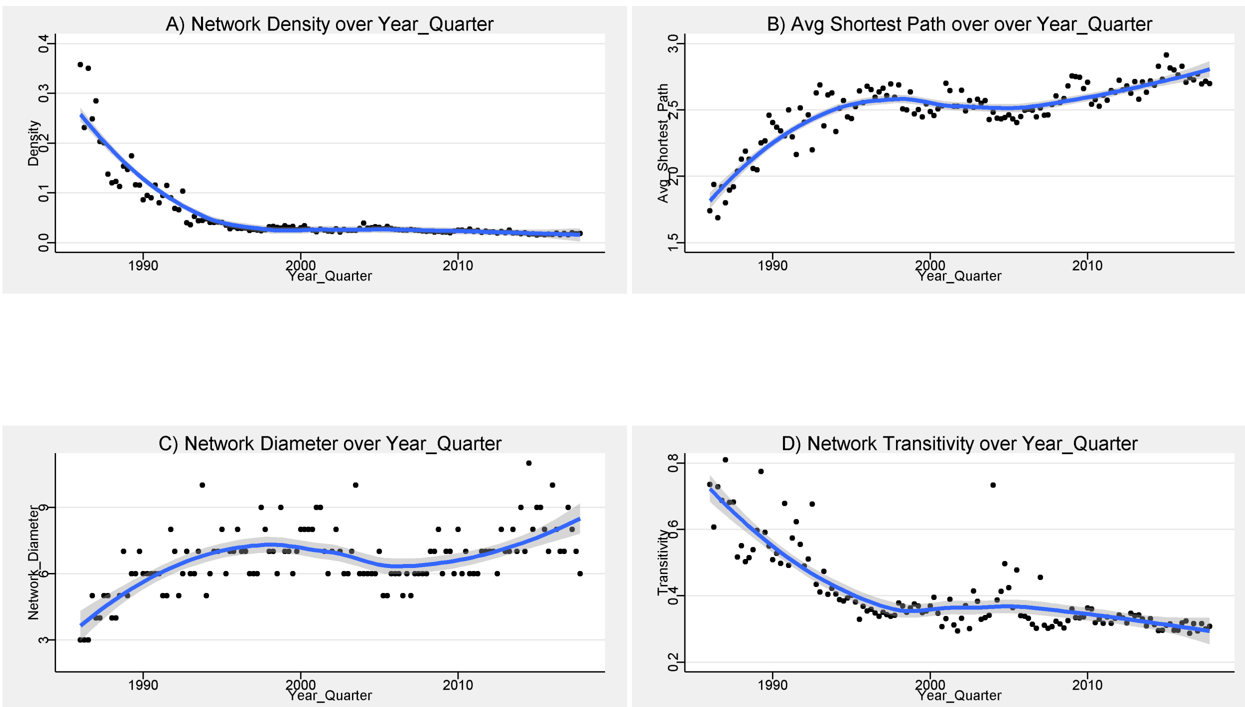


Table 2: Sample selection

	Facilities	Packages	Lenders	Borrowers	Comment
1	344, 953	237, 028	20, 196	87, 909	Global Syndicate Sample
2	338, 673	233, 198	11, 526	86, 318	Keep lead roles only
3	338, 673	233, 198	6, 317	86, 318	Keep one lead arranger only
4	102, 710	73, 656	3, 077	17, 447	Link to compustat withing 720 days prior to dealactivedate
5	76, 864	52, 732	2, 626	13, 375	Remove finance and utilities
6	69, 254	48, 141	2, 409	12, 494	Keep only USD denominated
7	68, 765	47, 794	2, 402	12, 453	Loans between 1987 and 2016
8	41, 447	28, 700	1, 583	8, 726	Require complete cases for main equation

Table 3: Descriptives: This table presents summary statistics for all variables in the sample of 41,447 loans from 1987 to 2016 used in the main analysis. Definitions of all variables are shown in Appendix A.

Summary Statistics:

VARIABLES	(1) N	(2) mean	(3) sd	(4) p25	(5) p50	(6) p75
Degree	41,447	0.192	0.131	0.0796	0.187	0.292
Betweennes	41,447	0.0137	0.0146	0.00107	0.00745	0.0256
Eigenvector	41,447	0.612	0.310	0.379	0.674	0.889
N_Score	41,447	7.597	2.435	6.368	8.522	9.519
Hi_Centrality	41,447	0.461	0.499	0	0	1
Spread	41,447	222.8	148.4	112.5	200	300
Leverage	41,447	0.308	0.223	0.147	0.281	0.428
AtLog	41,447	6.556	2.040	5.115	6.556	7.954
Tangibility	41,447	0.446	0.238	0.261	0.445	0.628
Roa	41,447	0.0142	0.129	-0.000463	0.0381	0.0726
Dloss	41,447	0.251	0.434	0	0	1
Capx_Intens	41,447	0.0650	0.0692	0.0227	0.0427	0.0793
AltmanZ	41,447	3.376	3.248	1.653	2.750	4.245
DInvG	41,447	0.195	0.396	0	0	0
Low_Numest	41,447	0.500	0.500	0	1	1
No_Rated	41,447	0.571	0.495	0	1	1
Has_Rd	41,447	0.409	0.492	0	0	1
NBig5	41,447	0.137	0.344	0	0	0
Opaque_Composite	41,447	1.745	1.158	1	2	3
LoanAmtLog	41,447	4.534	1.743	3.258	4.615	5.787
MatLog	41,447	3.693	0.699	3.367	4.060	4.111
DPerfpricing	41,447	0.357	0.479	0	0	1
NLenders	41,447	1.776	0.884	0.693	1.792	2.398
DSecured	41,447	0.574	0.495	0	1	1
DCovenants	41,447	0.507	0.500	0	1	1
BH_Reputation	41,447	0.518	0.500	0	1	1
BH_MarketShare	41,447	0.0737	0.0635	0.0147	0.0544	0.120
LA_Reputation	41,447	0.467	0.499	0	0	1
Relationship	41,447	0.340	0.474	0	0	1
New_Indus	41,447	0.195	0.396	0	0	0
New_Geo	41,447	0.149	0.356	0	0	0
Not_LocalLead	31,855	0.807	0.395	1	1	1
New_Firm	41,447	0.154	0.361	0	0	0
Default	22,141	0.0585	0.235	0	0	0

Table 4: The effect of lead centrality on loan spread - Each observation in the analysis corresponds to one loan facility. The dependent variable in columns 1 through 5 is *Spread*, the interest margin over the LIBOR (London Interbank Offered Rate) for each loan. The main coefficient of interest is that on *Centrality*. *Centrality* measures the wellconnectedness of the lead arranger in the network of past syndicate collaborations. Lead centrality is measured by *Degree* in column (1), by *Eigenvector* in column (2), by *Betweenness* in column (3), and by *NScore* in columns (4) and (5). *NScore* is the average of the yearly percentile ranks of each of the raw centrality scores (i.e, *Degree*, *Betweenness* and *Eigenvector*). All specifications include Firm, Loan and Lender level control variables as well as fixed effects for the purpose of the loan, *Loan_Purpose*; for whether the syndicate has more than one lender with a lead role, *Multi_Lead*; and the year of the loan initiation, *Year_FE*. Columns (1) through (4) include industry fixed effects *Indus_FE*; while column (5) includes borrower fixed effects *Firm_FE*. Appendix A presents a detailed description of all the variables. t-statistics (in parentheses) in all regressions are based on standard errors clustered by firm. *, **, *** indicate significance at the 10%, 5% and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)
	Deg	*Eigenv*	*Betw*	*NScore*	*NScore*
Centrality	−74.186***	−38.663***	−23.835***	−5.321***	−4.584***
	(−10.11)	(−12.68)	(−4.25)	(−14.18)	(−10.93)
MatLog	−12.542***	−12.473***	−13.055***	−12.235***	−9.082***
	(−10.13)	(−10.07)	(−10.52)	(−9.87)	(−7.34)
LoanAmtLog	−17.082***	−16.961***	−17.621***	−16.843***	−16.885***
	(−18.41)	(−18.34)	(−18.92)	(−18.22)	(−17.98)
NLenders	−1.877	−1.848	−2.504*	−2.012	−2.994**
	(−1.46)	(−1.44)	(−1.95)	(−1.57)	(−2.22)
DPerfpricing	−27.147***	−26.340***	−27.018***	−25.881***	−24.560***
	(−16.08)	(−15.59)	(−15.99)	(−15.32)	(−13.91)
DSecured	54.830***	54.321***	55.426***	54.033***	37.803***
	(30.89)	(30.63)	(31.22)	(30.50)	(18.62)
DCovenants	−10.962***	−11.183***	−10.601***	−11.273***	−6.409***
	(−5.49)	(−5.61)	(−5.30)	(−5.67)	(−3.15)
DtermB	49.499***	50.360***	49.131***	50.511***	36.792***
	(16.55)	(16.83)	(16.43)	(16.89)	(12.79)
Drevolver	−37.040***	−36.863***	−37.227***	−36.732***	−37.631***
	(−23.97)	(−23.89)	(−24.01)	(−23.85)	(−26.01)
Leverage	51.899***	52.570***	51.523***	53.017***	41.104***

	(10.77)	(10.92)	(10.67)	(11.01)	(6.51)
AtLog	−8.408***	−8.268***	−8.938***	−8.135***	−8.563***
	(−8.75)	(−8.62)	(−9.21)	(−8.48)	(−5.36)
Tangibility	−15.515***	−15.760***	−14.615***	−15.754***	−8.758
	(−2.90)	(−2.95)	(−2.73)	(−2.96)	(−1.00)
Roa	−77.077***	−76.037***	−77.470***	−75.181***	−69.989***
	(−7.90)	(−7.82)	(−7.90)	(−7.75)	(−5.95)
Dloss	40.766***	40.524***	40.879***	40.461***	30.665***
	(16.66)	(16.58)	(16.66)	(16.55)	(11.93)
Capx_Intens	−28.709*	−28.687*	−28.633*	−28.671*	−56.914***
	(−1.74)	(−1.73)	(−1.74)	(−1.73)	(−3.10)
AltmanZ	−2.583***	−2.555***	−2.607***	−2.546***	−2.624***
	(−8.34)	(−8.27)	(−8.37)	(−8.27)	(−6.54)
DInvG	−16.498***	−16.933***	−15.547***	−17.254***	−17.832***
	(−6.68)	(−6.85)	(−6.26)	(−6.99)	(−4.87)
Relationship	−3.741***	−2.610*	−5.567***	−2.217	−2.620**
	(−2.71)	(−1.89)	(−4.05)	(−1.61)	(−1.99)
BH_Repu	−11.276***	−10.427***	−14.328***	−10.025***	−11.783***
	(−7.08)	(−6.57)	(−8.90)	(−6.34)	(−6.46)
Observations	41447	41447	41447	41447	41447
Adjusted R^2	0.548	0.550	0.546	0.551	0.660
Fixed Effects					
L_Purpose	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Multi_Lead	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Year_FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Indus_FE	*Yes*	*Yes*	*Yes*	*Yes*	
Firm_FE					*Yes*

Table 5: Robustness of the effect of lead centrality on loan spread - Each observation in the analysis corresponds to one loan facility. The dependent variable in columns 1 through 4 in both panel A and panel B is *Spread*, the interest margin over the LIBOR (London Interbank Offered Rate) for each loan. The main coefficient of interest is that on *Centrality* in all columns except for columns (2) and (3) in Panel B in which the coefficient of interest is that on *Hi_Centrality*. *Centrality* measures the well-connectedness of the lead arranger in the network of past syndicate collaborations. Lead centrality is measured by *NScore* in all specifications. *NScore* is the average of the yearly percentile ranks of each of the raw centrality scores (i.e, *Degree*, *Betweenness* and *Eigenvector*). *Hi_Centrality* is an indicator variable that equals 1 when *NScore* is above the sample median in each year. All specifications include Firm-, Loan- and Lender- level control variables as well as fixed effects for the purpose of the loan, *Loan_Purpose*; for whether the syndicate has more than one lender with a lead role, *Multi_Lead*; and the year of the loan initiation, *Year_FE*.

Panel A reports results of plausible variations of equation 5. Column (1) in Panel A uses an alternative control variable for lead arranger reputation by replacing *BH_Reputation*, an indicator variable that takes a value of 1 if the lenders bank holding company is either *"Bank of America Merrill Lynch"*, *"JP Morgan"* or *"Citi"*, or any of their predecessors (based on Ross (2010); with a measure of the market share of the lead arrangers' bank holding company in the year prior to the loan origination, *BH_MktShare*. Column (2) in Panel A estimates equation 5 but uses an alternative control variable for lead arranger reputation by replacing *BH_Reputation*, with *LA_Reputation*, an indicator variable that takes a value of one if the lead arranger has a market share greater than 2% in the year prior to loan origination (based on Bushman and Wittenberg-Moerman (2012)). Column (3) estimates equation 5 but excludes observations in which more than one lender in the syndicate have a lead role. Column (4) estimates equation 5 but excludes observations in which the lead arrangers' bank holding company is either *"Bank of America Merrill Lynch"*, *"JP Morgan"* or *"Citi"*, or any of their predecessors.

	(1)	(2)	(3)	(4)
	BH_MktSh	*LA_Repu*	*Multi_Lead=0*	*BH_Repu=0*
Centrality	-5.416^{***}	-6.331^{***}	-7.048^{***}	-5.876^{***}
	(−9.72)	(−9.36)	(−11.38)	(−10.31)
Observations	41447	41447	20278	19993
Adjusted R^2	0.551	0.550	0.505	0.495
Controls	*Yes*	*Yes*	*Yes*	*Yes*
Fixed Effects				
L_Purpose	*Yes*	*Yes*	*Yes*	*Yes*
Multi_Lead	*Yes*	*Yes*	*Yes*	*Yes*
Year_FE	*Yes*	*Yes*	*Yes*	*Yes*
Indus_FE	*Yes*	*Yes*	*Yes*	*Yes*

Panel B reports results of alternative specifications to test for the effect of lead centrality on spread. Column (1) in panel B includes lead lender fixed effects; *Bank_FE*. Column (2) in panel B replaces the dependent variable of interest, *Centrality* with a dichotomous variable *Hi_Centrality*. Column (3) corresponds to a specification that uses entropy balancing to ensure covariate balance between treatment (i.e., *Hi_Centrality* = 1) and control groups (i.e., *Hi_Centrality* = 0). Column (4) estimates equation 5 but only for borrowing firms with a credit rating and using a much more restrictive fixed effects structure. Specificaly, *IRI_FE* includes *Industry* × *Rating* × *Year* fixed effects. Appendix A presents a detailed description of all the variables. tstatistics (in parentheses) in all regressions are based on standard errors clustered by firm. *, **, *** indicate significance at the 10%, 5% and 1% level, respectively.

	(1)	(2)	(3)	(4)
	Lead_FE	*Hi_Cent*	*Entropy*	*IRY_FE*
Centrality	−3.833***			−3.214***
	(−4.92)			(−3.44)
Hi_Centrality		−9.676***	−8.307***	
		(−4.88)	(−4.51)	
Observations	41447	41447	41447	17769
Adjusted R^2	0.606	0.547	0.567	0.707
Controls	*Yes*	*Yes*	*Yes*	*Yes*
Fixed Effects				
L_Purpose	*Yes*	*Yes*	*Yes*	*Yes*
Multi_Lead	*Yes*	*Yes*	*Yes*	*Yes*
Year_FE	*Yes*	*Yes*	*Yes*	
Indus_FE	*Yes*	*Yes*	*Yes*	
Bank_FE	*Yes*			
IRY_FE				*Yes*

Table 6: The effect of lead centrality on nonprice loan characteristics - Each observation in the analysis corresponds to one loan facility. In panel A, the dependent variable is the natural logarithm of the loan amount, *LoanAmtLog*, in columns (1) and (2) and the natural logarithm of the loan maturity in months, *MatLog*, in columns (3) and (4). In panel B, the dependent variable is an indicator variable of whether the deal has a covenant, *Dcovenant*, in columns (1) and (2) and an indicator variable of whether the deal has is Secured, *DSecured*, in columns (3) and (4). The main coefficient of interest is that on *Centrality*. *Centrality* measures the well-connectedness of the lead arranger in the network of past syndicate collaborations, measured as *NScore* in all columns. All specifications include Firm-, Loan- and Lender- level control variables as well as fixed effects for the purpose of the loan, *Loan_Purpose*; for whether the syndicate has more than one lender with a lead role, *Multi_Lead*; and the year of the loan initiation, *Year_FE*. Columns (1), (3) include industry fixed effects *Indus_FE*; while columns (2), (4) include borrower fixed effects *Firm_FE*. Appendix A presents a detailed description of all the variables. t-statistics (in parentheses) in all regressions are based on standard errors clustered by firm. *, **, *** indicate significance at the 10%, 5% and 1% level, respectively.

Panel A - Loan Amounts and Maturities

	(1)	(2)	(3)	(4)
	LoanAmtLog	*LoanAmtLog*	*MatLog*	*MatLog*
Centrality	0.033***	0.027***	0.016***	0.010***
	(10.61)	(8.07)	(8.25)	(4.46)
Observations	41447	41447	41447	41447
Adjusted R^2	0.75	0.79	0.28	0.38
Controls	*Yes*	*Yes*	*Yes*	*Yes*
Fixed Effects				
Purpose_FE	*Yes*	*Yes*	*Yes*	*Yes*
Multi_Lead	*Yes*	*Yes*	*Yes*	*Yes*
Year_FE	*Yes*	*Yes*	*Yes*	*Yes*
Indus_FE	*Yes*		*Yes*	
Firm_FE		*Yes*		*Yes*

Panel B - Covenants and Collateral

	(1) *DCovenants*	(2) *DCovenants*	(3) *DSecured*	(4) *DSecured*
Centrality	-0.006^{***}	-0.006^{***}	-0.011^{***}	-0.008^{***}
	(-4.53)	(-3.97)	(-8.67)	(-5.07)
Observations	41447	41447	41447	41447
Adjusted R^2	0.49	0.59	0.36	0.52
Controls	*Yes*	*Yes*	*Yes*	*Yes*
Fixed Effects				
Purpose_FE	*Yes*	*Yes*	*Yes*	*Yes*
Multi_Lead	*Yes*	*Yes*	*Yes*	*Yes*
Year_FE	*Yes*	*Yes*	*Yes*	*Yes*
Indus_FE	*Yes*		*Yes*	
Firm_FE		*Yes*		*Yes*

Table 7: The effect of lead centrality on spread conditional on measures of borrower transparency - I separately examine the effect of lead centrality on loan spread for sub-samples of high and low transparency borrowers. The dependent variable in all columns is *Spread*, the interest margin over the LIBOR (London Interbank Offered Rate) for each loan. The main coefficient of interest is that on *Centrality* in all columns, which measures the well-connectedness of the lead arranger in the network of past syndicate collaborations. Lead centrality is measured by *NScore*, which is the average of the yearly percentile ranks of each of the raw centrality scores (i.e, *Degree*, *Betweenness* and *Eigenvector*). In panel A columns (1) and (2) I separately examine sub-samples of high and low number of analyst following the firm, respectively. High analyst following corresponds to the sub-sample of borrowers with above median number of analyst following the firm in each year of my sample. The number of analyst following are calculated in the year prior to the loan origination. In panel A columns (3) and (4) I separately examine sub-samples of borrowers with and without a long term credit rating, respectively. In panel B columns (1) and (2) I separately examine borrowers in industries other than *HighTech* and borrowers in *High Tech*, respectively (based on Chuluun (2015)). In panel B columns (3) and (4) I separately examine sub-samples of borrowers without positive R&D expenditures and borrowers with positive R&D expenditures in the year prior to loan origination, respectively. In panel C columns (1) and (2) I separately examine sub-samples of borrowers audited by Big5 Audit firms and borrowers not audited by a Big5 Audit firm in the year prior to loan origination, respectively. All specifications include Firm-, Loan- and Lender- level control variables as well as fixed effects for the purpose of the loan, *Loan_Purpose*; for whether the syndicate has more than one lender with a lead role, *Multi_Lead*; the year of the loan initiation, *Year_FE*, and industry fixed effects; *Indus_FE*, with the exception of columns (1) and (2) in Panel B that exclude the industry fixed effects. Appendix A presents a detailed description of all the variables. t-statistics (in parentheses) in all regressions are based on standard errors clustered by firm. *, **, *** indicate significance at the 10%, 5% and 1% level, respectively.

Panel A - Analyst following and Ratings

	(1) *High Analyst*	(2) *Low Analyst*	(3) *Rated*	(4) *Not Rated*
Centrality	-3.286^{***}	-6.024^{***}	-3.059^{***}	-6.140^{***}
	(-5.88)	(-12.22)	(-4.70)	(-13.44)
Observations	20723	20724	17769	23678
Adjusted R^2	0.588	0.442	0.621	0.489
Controls	*Yes*	*Yes*	*Yes*	*Yes*
Fixed Effects				
L_Purpose	*Yes*	*Yes*	*Yes*	*Yes*
Multi_Lead	*Yes*	*Yes*	*Yes*	*Yes*
Year_FE	*Yes*	*Yes*	*Yes*	*Yes*
Indus_FE	*Yes*	*Yes*	*Yes*	*Yes*
Sample split	$\tilde{\chi}^2$	*p-value*	$\tilde{\chi}^2$	*p-value*
Centrality	15.833	0.000	15.243	0.000

Panel B - High Tech and R&D

	(1) *Not High Tech*	(2) *High Tech*	(3) *No R&D*	(4) *Has R&D*
Centrality	-4.999^{***}	-6.909^{***}	-3.951^{***}	-7.466^{***}
	(-12.33)	(-7.31)	(-8.19)	(-12.64)
Observations	36137	5310	24515	16932
Adjusted R^2	0.551	0.563	0.526	0.593
Controls	*Yes*	*Yes*	*Yes*	*Yes*
Fixed Effects				
L_Purpose	*Yes*	*Yes*	*Yes*	*Yes*
Multi_Lead	*Yes*	*Yes*	*Yes*	*Yes*
Year_FE	*Yes*	*Yes*	*Yes*	*Yes*
Indus_FE	*Yes*	*Yes*	*Yes*	*Yes*
Sample split	$\tilde{\chi}^2$	*p-value*	$\tilde{\chi}^2$	*p-value*
Centrality	3.496	0.061	21.382	0.000

Panel C - Big 5 Auditor

	(1)	(2)
	Big 5 Audit	*Non Big 5 Audit*
Centrality	-4.873^{***}	-6.892^{***}
	(-11.82)	(-7.44)
Observations	35753	5694
Adjusted R^2	0.556	0.507
Controls	*Yes*	*Yes*
Fixed Effects		
Loan_Purpose	*Yes*	*Yes*
Multi_Lead	*Yes*	*Yes*
Year_FE	*Yes*	*Yes*
Indus_FE	*Yes*	*Yes*
Sample split	$\tilde{\chi}^2$	*p-value*
Centrality	4.039	0.044

Table 8: The effect of lead centrality on spread conditional on measures of ex-ante lead expertise - I separately examine the effect of lead centrality on loan spread for sub-samples of high and low lead arranger expertise. The dependent variable in all columns is *Spread*, the interest margin over the LIBOR (London Interbank Offered Rate) for each loan. The main coefficient of interest is that on *Centrality* in all columns, which measures the well-connectedness of the lead arranger in the network of past syndicate collaborations. Lead centrality is measured by *NScore*, which is the average of the yearly percentile ranks of each of the raw centrality scores (i.e, *Degree*, *Betweenness* and *Eigenvector*). In panel A columns (1) and (2) I separately examine sub-samples of loans arranged by *Relationship* banks vs *Non Relationship* banks. A lead arranger is a *Relationship* bank when it has had a lead role in some other loan by the same borrower in the five years prior to the loan initiation date. In panel A columns (3) and (4) I separately examine sub-samples of loans arranged by banks with industry expertise vs banks with no industry expertise. A lead bank is considered to have no industry expertise when it is the first time that it arranges a loan for a borrower in the same two digit sic code over the five years prior to the loan origination. In panel B columns (1) and (2) I separately examine sub-samples of loans arranged by banks with geography expertise vs banks with no geography expertise. A lead bank is considered to have no geography expertise when it is the first time that it arranges a loan for a borrower in the same state over the five years prior to the loan origination. In panel B columns (3) and (4) I separately examine sub-samples of loans arranged by banks headquartered in the same state as the borrower vs banks headquartered in a different state than the borrower. All specifications include Firm-, Loan- and Lender- level control variables as well as fixed effects for the purpose of the loan, *Loan_Purpose*; for whether the syndicate has more than one lender with a lead role, *Multi_Lead*; the year of the loan initiation, *Year_FE*, and industry fixed effects; *Indus_FE*. Appendix A presents a detailed description of all the variables. t-statistics (in parentheses) in all regressions are based on standard errors clustered by firm. *, **, *** indicate significance at the 10%, 5% and 1% level, respectively.

Panel A - Relationship and Industry prior experience

	(1) *Relationship*	(2) *No Relationship*	(3) *No NewIndus*	(4) *NewIndus*
Centrality	−3.071***	−5.939***	−4.599***	−7.956***
	(−3.85)	(−14.84)	(−8.91)	(−11.28)
Observations	14103	27344	32917	8073
Adjusted R^2	0.588	0.526	0.566	0.500
Controls	*Yes*	*Yes*	*Yes*	*Yes*
Fixed Effects				
L_Purpose	*Yes*	*Yes*	*Yes*	*Yes*
Multi_Lead	*Yes*	*Yes*	*Yes*	*Yes*
Year_FE	*Yes*	*Yes*	*Yes*	*Yes*
Indus_FE	*Yes*	*Yes*	*Yes*	*Yes*
Sample split	$\tilde{\chi}^2$	*p-value*	$\tilde{\chi}^2$	*p-value*
Centrality	11.484	0.001	15.688	0.000

Panel B - Geography prior experience

	(1)	(2)	(3)	(4)
	Not New Geo	*New Geo*	*Same state*	*Out of State*
Centrality	−3.998***	−7.963***	−3.867***	−7.447***
	(−8.33)	(−10.42)	(−4.60)	(−13.15)
Observations	32531	6161	6158	25697
Adjusted R^2	0.565	0.499	0.555	0.577
Controls	*Yes*	*Yes*	*Yes*	*Yes*
Fixed Effects				
Loan_Purpose	*Yes*	*Yes*	*Yes*	*Yes*
Multi_Lead	*Yes*	*Yes*	*Yes*	*Yes*
Year_FE	*Yes*	*Yes*	*Yes*	*Yes*
Indus_FE	*Yes*	*Yes*	*Yes*	*Yes*
Sample split	$\tilde{\chi}^2$	*p-value*	$\tilde{\chi}^2$	*p-value*
Centrality	20.769	0.000	12.770	0.000

APPENDIX E - TABLES IN ADDITIONAL ANALYSIS

Table 9: Lead centrality and skin in the game - This table reports the results of OLS regressions investigating the effect of lead centrality on the fraction of the loan held by the lead arranger at origination. Each observation in the analysis corresponds to one loan facility. The dependent variable in all columns is *% Loan Held by Lead*. I include Firm, Loan and Lender level control variables as well as fixed effects for whether the syndicate has more than one lender with a lead role, *Multi_Lead*; the year of the loan initiation, *Year_FE* and industry fixed effects *Indus_FE*. Appendix A presents a detailed description of all the variables. t-statistics (in parentheses) in all regressions are based on standard errors clustered by firm. *, **, *** indicate significance at the 10%, 5% and 1% level, respectively.

	(1)	(2)	(3)
	% Held by Lead	*% Held by Lead*	*% Held by Lead*
Centrality	-0.787^{***}	-0.626^{***}	-0.145
	(-9.86)	(-4.77)	(-0.87)
Opaque_Composite			2.154^{***}
			(4.22)
Centrality* × *Opaque_Composite			-0.292^{***}
			(-4.61)
Observations	15468	15468	15468
Adjusted R^2	0.837	0.888	0.837
Controls	*Yes*	*Yes*	*Yes*
Fixed Effects			
Loan_Purpose	*Yes*	*Yes*	*Yes*
Multi_Lead	*Yes*	*Yes*	*Yes*
Year_FE	*Yes*	*Yes*	*Yes*
Indus_FE	*Yes*		*Yes*
Firm_FE		*Yes*	

Table 10: The effect of lead centrality on spread in a sample with low within syndicate information asymmetries - This table reports the results of OLS regressions investigating the effect of lead centrality on loan spread in a sub sample of loans and firms where there likely are no within-syndicate information asymmetries. Each observation in the analysis corresponds to one loan facility. The dependent variable in columns 1 through 4 is *Spread*, the interest margin over the LIBOR (London Interbank Offered Rate) for each loan. Columns (1) and (2) estimate equation 5 in a sub-sample of *New Firms*, that is, loans that are within 3 years of the firms IPO date. Columns (3) and (4) estimate equation *Spread* for a sub-sample of loans where the lead bank keeps 100% of the loan at origination. The main coefficient of interest is that on *Centrality*. *Centrality* measures the wellconnectedness of the lead arranger in the network of past syndicate collaborations. Lead centrality is measured by *NScore* in all columns. *NScore* is the average of the yearly percentile ranks of each of the raw centrality scores (i.e, *Degree*, *Betweenness* and *Eigenvector*). All specifications include Firm, Loan and Lender level control variables as well as fixed effects for the purpose of the loan, *Loan_Purpose*; for whether the syndicate has more than one lender with a lead role, *Multi_Lead*; and the year of the loan initiation, *Year_FE*. Columns (1) and (3) include industry fixed effects *Indus_FE*; while columns (2) and (4) includes borrower fixed effects *Firm_FE*. Appendix A presents a detailed description of all the variables. t-statistics (in parentheses) in all regressions are based on standard errors clustered by firm. *, **, *** indicate significance at the 10%, 5% and 1% level, respectively.

	(1)	(2)	(3)	(4)
	New_Firms	*New_Firms*	*Sole_Lender*	*Sole_Lender*
Centrality	-5.488^{***}	-6.365^{***}	-8.530^{***}	-5.401^{***}
	(−6.70)	(−4.59)	(−11.38)	(−4.64)
Observations	6376	6376	5945	5945
Adjusted R^2	0.453	0.702	0.425	0.680
Controls	*Yes*	*Yes*	*Yes*	*Yes*
Fixed Effects				
Loan_Purpose	*Yes*	*Yes*	*Yes*	*Yes*
Multi_Lead	*Yes*	*Yes*	*Yes*	*Yes*
Year_FE	*Yes*	*Yes*	*Yes*	*Yes*
Indus_FE	*Yes*		*Yes*	
Firm_FE		*Yes*		*Yes*

Table 11: Ex-Post Loan Performance - This table reports the results of OLS regressions investigating the effect of lead centrality on loan default. The dependent variable is *Default*. The main coefficient of interest is that on *Centrality*. *Centrality* measures the wellconnectedness of the lead arranger in the network of past syndicate collaborations. Lead centrality is measured by *NScore*. *NScore* is the average of the yearly percentile ranks of each of the raw centrality scores (i.e, *Degree*, *Betweenness* and *Eigenvector*). I include Firm, Loan and Lender level control variables as well as fixed effects for whether the syndicate has more than one lender with a lead role, *Multi_Lead*; the year of the loan initiation, *Year_FE* and industry fixed effects *Indus_FE*. Appendix A presents a detailed description of all the variables. t-statistics (in parentheses) in all regressions are based on standard errors clustered by firm. *, **, *** indicate significance at the 10%, 5% and 1% level, respectively.

	(1)
	Loan_Default
Centrality	-0.003^{**}
	(-2.42)
Observations	22141
Adjusted R^2	0.125
Controls	*Yes*
Fixed Effects	
Multi_Lead	*Yes*
Year_FE	*Yes*
Indus_FE	*Yes*

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